DISSERTATION

INNOVATIVE HYDROGEN STATION OPERATION STRATEGIES TO INCREASE AVAILABILITY AND DECREASE COST

Submitted by

Jennifer Kurtz

Department of Systems Engineering

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Doctoral Committee:

Advisor: Thomas Bradley

Bryan Willson
Siddharth Suryanarayanan
Mehmet Ozbek

ABSTRACT

INNOVATIVE HYDROGEN STATION OPERATION STRATEGIES TO INCREASE AVAILABILITY AND DECREASE COST

Major industry, government, and academic teams have recently published visions and objectives for widespread use of hydrogen in order to enable international energy sector goals such as sustainability, affordability, reliability, and security. Many of these visions emphasize the important and highly-scalable use of hydrogen in fuel cell electric cars, trucks, and buses, supported by public hydrogen stations. The hydrogen station is a complicated system composed of various storage, compression, and dispensing sub-systems, with the hydrogen either being delivered via truck or produced on-site.

As the number of fuel cell electric vehicles (FCEVs) on roads in the U.S. have increased quickly, the number of hydrogen stations, the amount of hydrogen dispensed, and the importance of their reliability and availability to FCEV drivers has also increased. For example, in California, U.S., the number of public, retail hydrogen stations increased from zero to more than 30 in less than 2 years, and the annual hydrogen dispensed increased from 27,400 kg in 2015 to nearly 105,000 kg in 2016, and more than 913,000 kg in 2018, an increase of nearly 9 times in 2 years for retail stations. So, although government, industry, and academia have studied many aspects of hydrogen infrastructure, much of the published literature does not address hydrogen station operational and system innovations even though FCEV and hydrogen stations have some documented problems with reliability, costs, and maintenance in this early commercialization

phase. In general, hydrogen station research and development has lagged behind the intensive development effort that has been allocated to hydrogen FCEVs.

Based on this understanding of the field, this research aims to identify whether integrating reliability engineering analysis methods with extensive hydrogen station operation and maintenance datasets can address the key challenge of station reliability and availability. The research includes the investigation and modeling of real-world hydrogen station operation and maintenance.

This research first documents and analyzes an extensive dataset of hydrogen station operations to discover the state-of-the-art of current hydrogen station capabilities, and to identify performance gaps with key criteria like cost, reliability, and safety. Secondly, this research presents a method for predicting future hydrogen demand in order to understand the impact of the proposed station operation strategies on data-driven decision-making for low-impact maintenance scheduling, and optimized control strategies. Finally, based on an analysis indicating the need for improved hydrogen station reliability, the research applies reliability engineering principles to the hydrogen station application through development and evaluation of a prognostic health management system.

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I want to thank my advisor, Dr. Thomas Bradley. Dr. Bradley has provided invaluable guidance along my education adventure, which made this a fulfilling experience. His thoughtful questions and comments provided me with direction, purpose, and clarity. Dr. Bradley graciously gave both motivation and technical guidance. I am grateful to have been able to complete this research with Dr. Bradley. And thank you to my committee members, Bryan Willson, Siddarth Suryanarayanan, and Mehmet Ozbek.

I want to thank my husband, Eric, and son, Andre. They have allowed me to follow a dream in the pursuit of this systems engineering degree and energy research that will make a positive impact on our world. Eric is my champion and calming motivator. Andre is joyful and full of life and a reminder for why the mission of a sustainable energy system is essential. To my parents, Dan and Marilyn, thank you for your never-ending belief that I can achieve all the dreams I have pursued. I don't know how I can ever say thank you enough. Wendy, Allison, and Nick are the finest siblings anyone could have, and I am thankful for you laughing and loving with me, and for well-timed nerd jokes whenever my ego got too big. To my mother-in-law, Eve, thank you for your contagious excitement and help keeping the family logistics going. And thank you to my friends and family that have provided more encouragement than I ever expected, especially as they have put up with me logging so many hours for this research and have been genuinely interested in the research (like you Scott). I am looking forward to saying yes to outings and new adventures with you all.

I would like to thank current and past colleagues at the National Renewable Energy Laboratory. Sam Sprik, Genevieve Saur, Mike Peters, Erin Winkler, Shaun Onorato, Spencer Gilleon, Gina Artese, and Chris Ainscough make up a world-class research team. I am grateful to work with each team member covering brainstorming sessions to down-in-the-details coding. You have all been essential to the completion of this research, contributing valuable analysis and insight into the status, progress, and challenges of hydrogen infrastructure for mobility. Thank you to my manager, Chris Gearhart. I strive to mimic your leadership and thank you for your encouragement. And thank you to Keith Wipke and Johney Green, for your support of the balance between my full-time job responsibilities and pursuit of this degree.

PREFACE

My professional career has been dedicated to hydrogen and fuel cell technologies because of the sustainability and technical benefits. It was a natural conclusion that my dissertation research would be centered around these technologies. My motivation grew from my professional research, collaborations with industry, and a realization that there was an opportunity to positively impact a critical infrastructure system needed to realize the benefits of hydrogen and fuel cell technologies. Pursuing a Systems Engineering PhD has enabled me to explore the value of integrated systems research and expand my horizons.

I completed this while leading a research team at the NREL. Because of this, I was able to leverage many collaborations necessary to complete this research. I would like to my National Fuel Cell Technology Evaluation Center (NFCTEC) team and the Fuel Cell Technology Office at DOE. My NREL research partners are Sam Sprik, Erin Winkler, Chris Gearhart, Mike Peters, and Chris Ainscough (formerly NREL). The work would not have been possible without the invaluable data from our hydrogen station industry partners. My advisor, Dr. Bradley, was essential in the research direction and completion. I have grown from his instruction and I've learned valuable lessons from his process and feedback.

With this experience, I am motivated to be a leader in integrated energy systems engineering research. As Justice Ruth Bader Ginsburg stated, "Fight for the things that you care about but do it in a way that will lead others to join you."

AUTOBIOGRAPHY

Jennifer Kurtz leads the Hydrogen and Fuel Cell Systems Engineering group at the National Renewable Energy Laboratory, which includes hydrogen and fuel cell activities in technology validation, safety, codes and standards, market transformation, hydrogen infrastructure, grid integration, analysis, and renewable hydrogen production. My team is approximately 25 staff with research portfolio covering system efficiency, lowering cost, and improving reliability of systems through analysis, experiments, and industry/agency partnerships. In this research portfolio, NREL also has a fully integrated research station, the Hydrogen Infrastructure Testing and Research Facility (HITRF), that includes all operational aspects from renewable hydrogen production to end use. NREL's HITRF serves as a test platform for innovative hydrogen infrastructure and integrated systems research.

As a principle research engineer for the National Fuel Cell Technology Evaluation Center, I process, analyze, and report on real-world data of fuel cell and hydrogen projects that span many markets such as vehicles, forklifts, hydrogen stations, and backup power. Prior to joining NREL, I worked at UTC Power primarily in fuel cell system design and components. I received my master's degree in mechanical engineering from Georgia Tech and my bachelor's degree in physics from Wartburg College.

DEDICATION

For my husband Eric and son, Andre.

"Do you know when you wonder, you are learning?" -Mr. Rogers

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1. Introduction to Hydrogen Infrastructure

Hydrogen infrastructure is a broad system of systems that are required for a hydrogen market. One way to illustrate a high-level hydrogen infrastructure is shown in Figure 1 from the vision of Hydrogen at Scale (H2@Scale) [1]. An example path through this hydrogen infrastructure is hydrogen production via electrolysis interfaced with the grid to produce for an end use like transportation, upgrading biomass, ammonia production, and metals refining. Details of each of these transitions, such as the dynamic grid control interface and hydrogen delivery, must also include the concept and function of hydrogen infrastructure. There are many active areas of research in hydrogen infrastructure, from the holistic systems-level integrations that are proposed in H2@Scale, to hydrogen material compatibility.

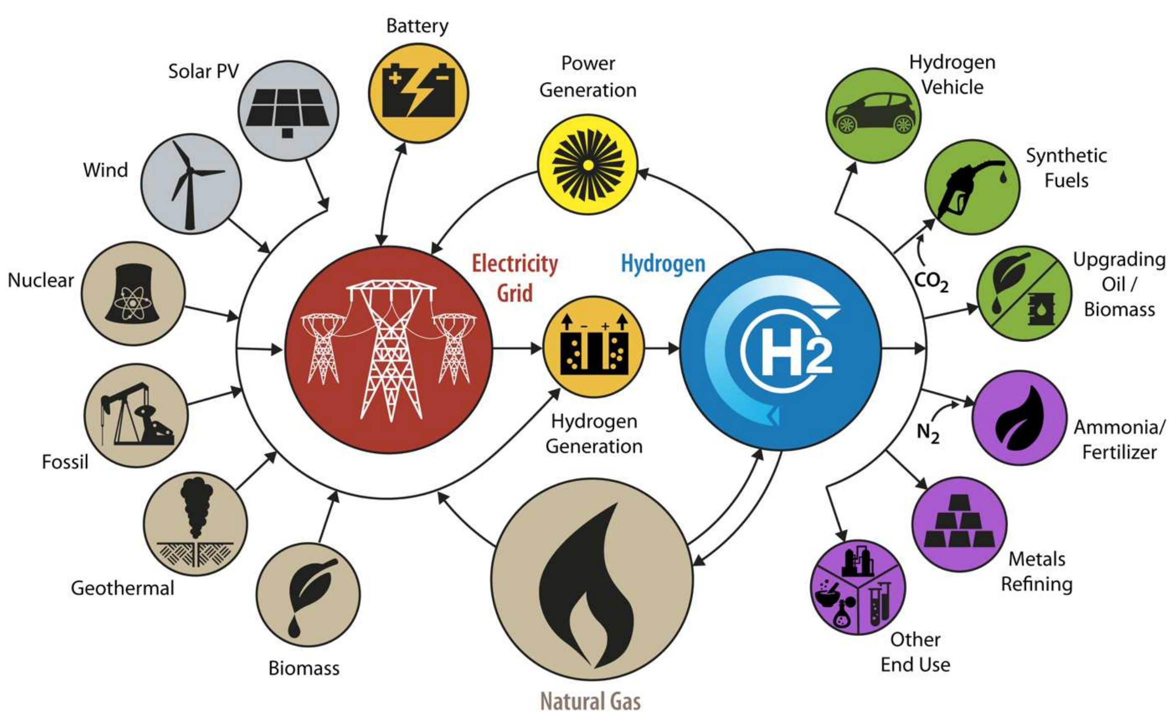

Figure 1. H2@Scale energy system illustration (not comprehensive)

This research focuses in on a critical and highly visible (i.e., directly interfacing with general consumers) subsystem of the hydrogen infrastructure system needed for transportation, specifically the hydrogen station for fueling fuel cell vehicles. This chapter reviews hydrogen infrastructure for transportation. The results of this review identify hydrogen station reliability as a key driver of hydrogen system operating expense.

Transportation is a major contributor to the productivity of the U.S. economy, but the pollution costs and economic costs of a petroleum-fueled transportation system are high. Transportation produced 57% of total nitrogen oxide emissions, 52% of carbon monoxide emissions, and 21% of total volatile organic compound emissions in the U.S. in 2016 [2]. Aggressive federal and state goals aim to reduce transportation emissions through regulation, improvements in existing technologies, and alternative transportation technologies. Three main objectives can be generalized from some U.S. transportation policies: 1) reduce greenhouse gas (GHG) emissions in the transportation sector, 2) diversify transportation energy sources to reduce petroleum consumption and promote U.S. energy security, and 3) reduce human health and environmental impacts from air pollution. Achieving these targets requires more than just improving the existing petroleum-fueled technologies. Alternative technologies such as battery, hydrogen, and biofuel vehicle technologies are understood to be required to realize deep emissions reductions within the transportation sector [3], [4].

Hydrogen-fueled vehicles, along with their associated hydrogen infrastructure, are a key component of an "all-of-the-above" strategy for reducing the environmental impacts of transportation. Hydrogen-fueled vehicles can be powered by either hydrogen internal combustion engine vehicle powertrains or fuel cell electric vehicle (FCEV) powertrains. FCEVs are the only hydrogen-fueled vehicles currently in production. In general, FCEVs are able to meet many of the environmental, policy, and consumer acceptability requirements of transportation. They are "zero-emission vehicles" [5] with low life-cycle GHG emissions [6], [7], long range and fast fueling [8], competitive market price (with lease and purchase options) [9], [10], [11], and durability [12]. As is widely understood, the beneficial characteristics of hydrogen-fueled vehicles are dependent on the lifecycle characteristics and function of their fueling infrastructure.

For example, the life cycle environmental impacts of hydrogen-fueled vehicles are highly dependent on the pathway by which the hydrogen is generated, transmitted, and delivered. Today, 95% of hydrogen produced in the U.S. is derived from natural gas via steam methane reforming. This is the most common and the most cost-effective method for hydrogen production. While producing hydrogen from natural gas is not aligned with long-term emissions reduction strategies, the current hydrogen pathway does reduce lifecycle emissions relative to conventional hydrocarbon fuels [13], [14], [15], [16]. In the long term, hydrogen production from water via electrolysis using renewable electricity has the potential to even further improve the economics and impacts of hydrogen-fueled transportation.

To introduce the technologies, systems, and economic characteristics of the hydrogen infrastructure that will enable FCEV technologies, this section reviews the state of the art in the U.S. for hydrogen infrastructure technologies, station roll-out, performance, and reliability. The emphasis is on developments in the past 10 years, although these developments are placed within historical context. However, the hydrogen infrastructure literature is relatively limited, as shown in Table 1. Research literature on fuel cells far exceeds the amount of research literature related to hydrogen infrastructure.

Table 1. Quantified Google Scholar search results, 2008–2018

Search Criteria ("allintitle")	*Results Count*
Fuel cell(s)	>23,000

Fuel cell vehicle(s)	>2,000
Hydrogen infrastructure (or station or stations)	~800
Hydrogen station(s) data	<10
Hydrogen station reliability	<5
Hydrogen station operation	~15
Hydrogen station costs	~15

This review of the state of the art of hydrogen infrastructure demonstration, performance, and commercialization is to propose an infrastructure operation-centric research agenda for increasing hydrogen infrastructure reliability and availability and reducing near-term costs.

1.1. Hydrogen Infrastructure for Transportation

Hydrogen is an energy carrier that can be produced from a variety of sources and can be converted into useful work via a variety of mechanisms. Hydrogen is a mass-produced industrial gas most commonly used in petroleum refining, ammonia production, and paper processing. The U.S. produces approximately 10 million metric tons of hydrogen a year, which would be enough hydrogen for approximately 50 million vehicles [17]. The steps necessary to supply hydrogen to the vehicle include production and delivery to the station (or production at the station), storage, compression, and dispensing. The systems that perform these functions are collectively referred to as transportation hydrogen infrastructure for the purpose of this review.

To generate useful motive power from stored hydrogen, hydrogen must be converted to mechanical work through either thermodynamic (e.g., internal combustion engine) or electrochemical/electromechanical means (e.g., FCEV and electric drivetrain). At present, FCEVs are the highest efficiency [18] and most production-ready hydrogen-to-energy technology available [19], and they will be the baseline vehicle technology considered for the remainder of this dissertation. Fuel cells consume hydrogen in an electrochemical reaction with oxygen to produce electricity, water, and heat. The most common hydrogen-fueled fuel cell system is a polymer electrolyte membrane (PEM) system, which includes subsystems for thermal management, hydrogen storage, electric powertrain, power electronics, and safety [20]. The fuel economy of an FCEV is typically 2–3 times higher than that of an internal combustion engine (e.g., 50–68 miles per gallon of gasoline equivalent compared with the EPA 24.7 miles per gallon model year 2016 average [21], [22]), and an FCEV has many of the same attributes (fueling time, range, mass, and size) as conventionally-fueled vehicles today. Effective FCEV applications are those that require these attributes, and fuel cells can enable many of the more general benefits of an electric-drive vehicle such as zero harmful tailpipe emissions (emitting mostly water, a small amount of hydrogen, and passing through nitrogen from the air), high performance, and quiet operation.

Some of the mobility applications available for fuel cells today include forklifts, airport ground support equipment, light- and heavy-duty vehicles, and public transit [23], [24]. Different vehicle types require different types of hydrogen infrastructure. Hydrogen is dispensed to vehicles at two different pressures: 35 MPa and 70 MPa. Light-duty passenger vehicles store gaseous hydrogen on-board with carbon-fiber-wrapped tanks that typically hold 4 to 6 kg of hydrogen at 70 MPa. The higher pressure is necessary to provide the light duty vehicles with a desirable range without sacrificing useable vehicle space (e.g., trunk and passenger areas). Other fuel cell vehicles, like buses, forklifts, and trucks, typically store hydrogen at 35 MPa. Light-duty FCEVs for personal and fleet applications have been in limited production since the early 2000s. Some FCEV manufacturers (Toyota, Hyundai, and Honda) are now selling commercial production vehicles [25], [26], [27]. Other manufacturers have been leasing pre-commercial FCEVs (Mercedes-Benz), have FCEVs in various development phases (GM and Nissan), or are in partnerships to develop commercial FCEVs.

In general, these long-term industrial investments in FCEV technologies have outpaced comparable types of investments in hydrogen infrastructure technologies. Hydrogen infrastructure, energy infrastructure, and FCEVs rely on one another for successful deployment, and many of the technological, consumer, and societal challenges with FCEVs involve the availability, reliability, and cost of hydrogen infrastructure.

1.1.1 Hydrogen Production Pathways

Hydrogen fuel pathways (Figure 2) are classified by hydrogen source (e.g., reformed methane, electrolyzed water). The pathways can also be categorized by the distribution mechanism (on-site generation or delivered). Various studies performed at universities, consultancies, and governments have considered the costs and benefits of different combinations of these pathways. The most relevant hydrogen pathways have been the subject of detailed analysis for their energy use and GHG emissions. Of the 10s of hydrogen pathways that might be considered scalable and relevant, hydrogen produced by central renewable electrolysis and delivered by pipeline is consistently found to have the lowest well-to-wheel GHG emissions [3], [28], [29], [30]. These studies also find that improvements in vehicle efficiency and fuel-path efficiency must both be realized to achieve long-term environmental and economic targets for hydrogen-fueled vehicles. These vehicle efficiency improvements will include mass reduction, aerodynamic improvements, and auxiliary load reductions. The hydrogen source must also be considered for an accurate understanding of the carbon intensity. Many researchers have published comparisons of hydrogen pathways to other vehicle and fuel pathways [6], [7], [14], [31], [32]. These studies show varying GHG emissions according to the various pathways and vehicle powertrain configurations, but in general, hydrogen-fueled FCEV GHG lifecycle emissions (g CO_{2e}/mi) are demonstrated to be 20%–70% lower than those of conventional petroleum-fueled vehicles.

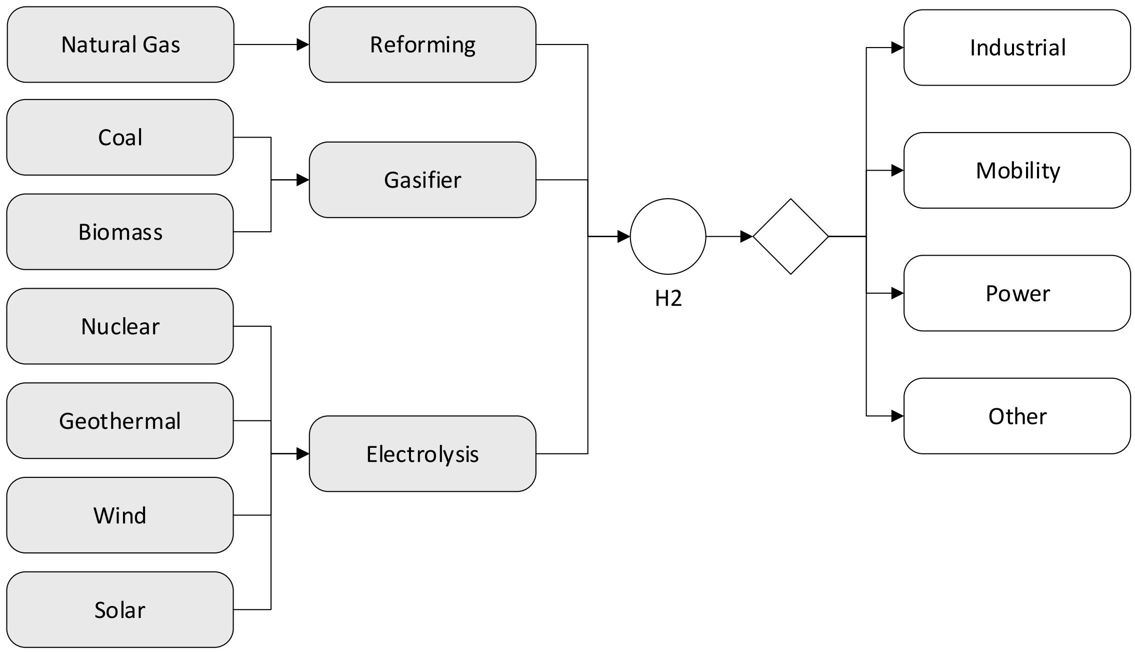

Figure 2. General hydrogen pathways

Hydrogen infrastructure for fueling FCEVs can be simplified into functions like source, make, store, move, use, and decision (as shown in Figure 3). The source function covers the beginning of the hydrogen production pathway and the make function covers the different production methods. Store and move network functions have similar attributes like hydrogen pressure and phase, but the difference is that the move function is dynamic, transporting hydrogen from one location to another. The decision function has a direct relationship to the other blocks because the attributes include safety, monitoring, and analysis. The use function is for the hydrogen fueling station, where a fill is completed with the transfer of gas happens from the station to the customer.

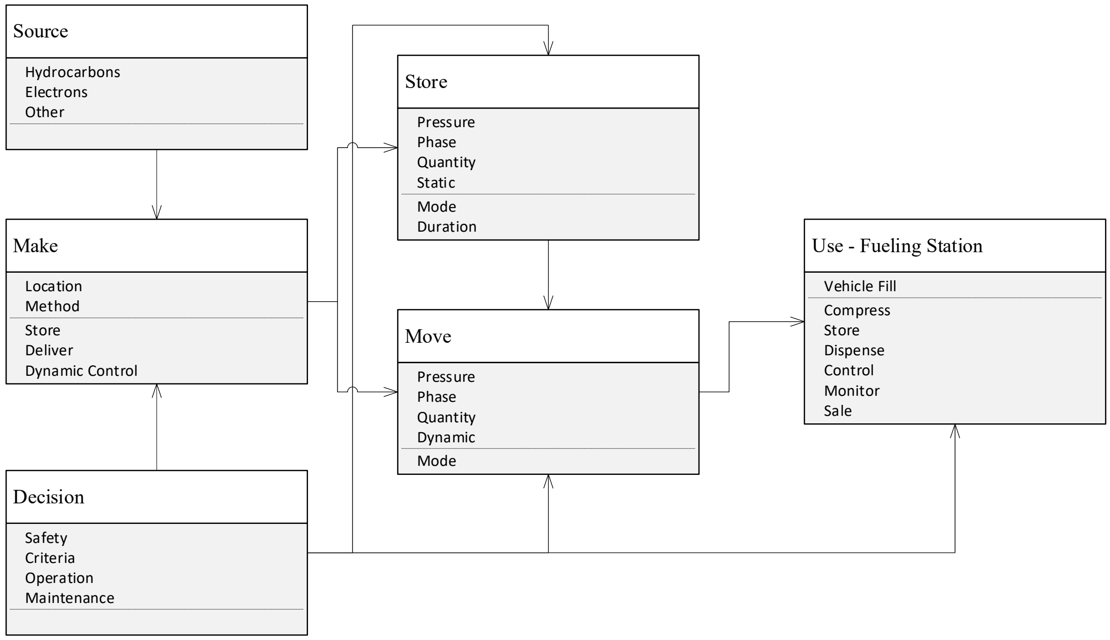

Figure 3. General hydrogen infrastructure for vehicle fueling

1.1.2 Hydrogen Station Types

There are many types of hydrogen stations that will be or have been deployed. The majority of current stations use delivered gaseous hydrogen from steam methane reforming [33]. This configuration is a result of commonality in station design and supply and minimizes costs at the scale of interest (see Figure 4 for the subsystems of a hydrogen station). The two leading categories of stations are 1) delivered hydrogen from steam methane reforming and 2) on-site hydrogen production via water electrolysis [33]. Delivered liquid hydrogen is likely to be a preferred hydrogen station storage option for a high throughput (i.e., kg/day) station and/or where space is limited. Other hydrogen pathway options utilized in low numbers today include delivered hydrogen produced from renewable sources and hydrogen delivery via pipeline [34], [35].

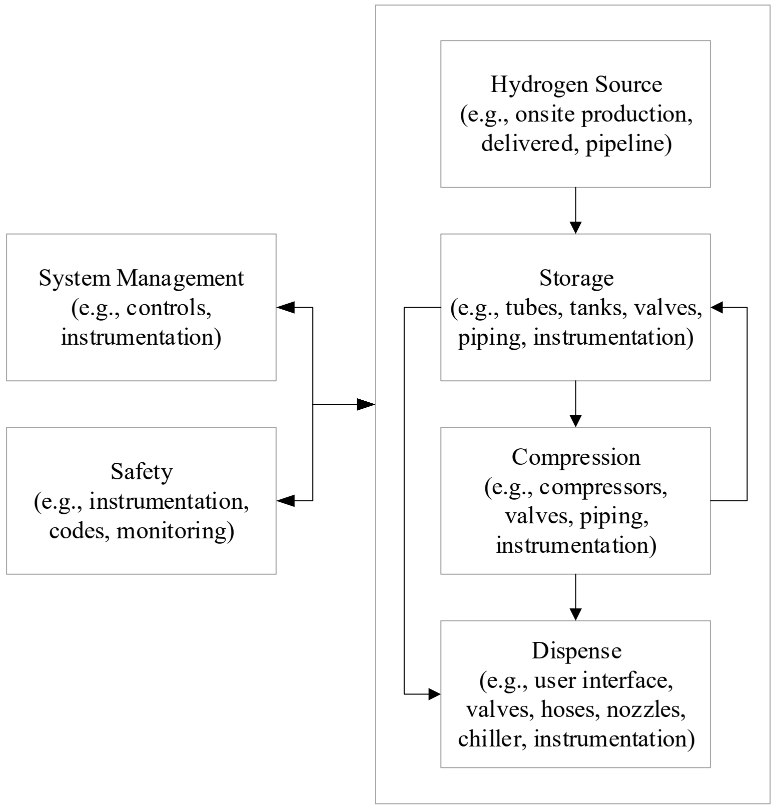

Figure 4. General hydrogen station subsystems diagram

1.1.3 Hydrogen Station Deployment

Because of the high costs of hydrogen infrastructure, planning and optimizing the hydrogen fueling system roll-out has been a key component of the community's research agenda [36]. Under the assumption that the quantity of hydrogen infrastructure may limit the adoption of hydrogen vehicle technologies in the near term, many studies have focused on comparisons to the history of gasoline station deployments [37] and on determining the optimal locations or timing of infrastructure roll-out to minimize costs or maximize the number of vehicles that can be served [38], [39], [40], [41], [42], [43], [44], [45], [46]. These studies have debated the costs and benefits of highway-centric infrastructure rollout plans, and or more concentrated infrastructure rollout plans, but in general, the rollout of hydrogen infrastructure in the US has incorporated aspects of both philosophies, as illustrated in Figure 3.

As of 2017, there are 35 public hydrogen stations in the U.S., with 34 stations in California [47] (Figure 5) supporting approximately 6,000 FCEVs. If private stations are included, there are 62 stations in the U.S. with another 26 stations planned. Hydrogen infrastructure is also expanding in the U.S. [48] and internationally, with 180 active stations outside of the U.S. [49], [50]. The State of California has established a near-term target of approximately 100 hydrogen stations in California, which is estimated to be a minimum hydrogen infrastructure network to support a near-term goal of 25,000–40,000 FCEVs in the state [51]. The California Fuel Cell Partnership has identified three priorities in order to realize 1,000 hydrogen stations and up to 1,000,000 vehicles by 2030: enable, establish, and expand the market [52].

Figure 5. Hydrogen stations in California, U.S., from the Alternative Fuels Data Center Alternative Fueling Station Locator (stations shown with blue circle points)

The process to build a hydrogen station from start to finish includes design, permitting, construction, and commissioning. These general steps can vary significantly in duration based on factors like site-specific challenges and local/multiple jurisdiction requirements [53]. Out of seven station construction timelines studied in NREL's National Fuel Cell Technology Evaluation Center (NFCTEC) in 2015, the permitting process for one station lasted 90 days, while for another it lasted 255 days. These long delays to a station's construction timeline can result in increased costs and risk. Decreasing the time for a station to go from design to retail fueling is being addressed through a number of activities such as the California Governor's Office of Business and Economic Development permit assistance, Hydrogen Station Permitting Guidebook [54], a collection of safety, codes, and standards guides [55], [56], [57], and the Hydrogen Station Equipment Performance Device [58]. In general, these efforts are working to disseminate information to builders and investors about hydrogen station construction, codes, and best practices.

1.1.4 Hydrogen Station Capital Costs

Hydrogen station capital costs are a challenge to the commercialization of hydrogen infrastructure. The primary source of data for understanding hydrogen station costs is the data collected for documentation of the California Energy Commission's (CEC's) cost sharing of station installation costs [59]. All CEC-funded stations (46 as of the end of 2015) record and publish their budgeted costs and actual costs (for stations that are either in operation or in development). Cost data collected from the CEC awards provide the low-volume basis for the economic evaluation of current stations (i.e., stations with capacity to dispense hundreds of kilograms per day instead of thousands of kilograms per day). At present, the lowest station cost is \$0.91 million and the highest station cost is \$4.6 million. The average station cost (from 46 stations) is $2.2 million, and the average breakdown of this cost is 5% for general/administration, 4% for data reporting (quarterly reporting on performance, operation, and maintenance to CEC and NFCTEC), 7% for commissioning, and 84% for the station itself, which includes equipment, engineering, fabrication, procurement, site preparation, construction, and installation. Another review of station installed costs, compares conventional station configurations with modular configurations [60], showing the authors expect to see more modular configurations in the future to reduce cost and station footprint.

As shown in Figure 6, the stations that have a common design and capacity have similar costs. The lowest-cost stations rely on delivered compressed gas with a minimum cost just under $1 million. The highest-cost stations have either relatively high daily capacity (e.g., 350 kg per day and station costs greater than $2.5 million) or on-site production (e.g., 100 kg per day and station costs greater than $3 million). The low-cost delivered gas stations and higher capacity liquid stations have capital costs of around $5,000 per daily capacity kilogram. This is a significant decrease from station capital costs in 2009, which exceeded $20,000 per daily capacity kilogram [61].

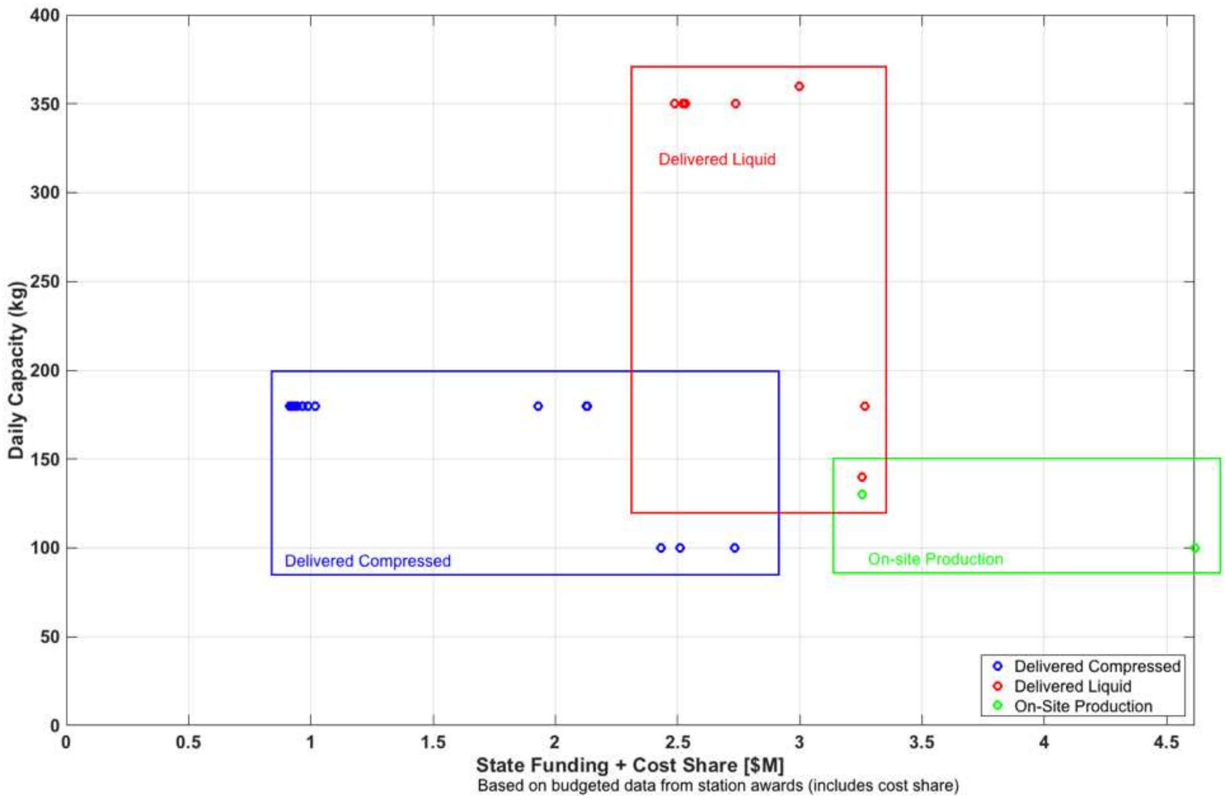

Figure 6. Station capital cost by daily capacity for CEC-funded stations

1.2. Conclusion

The development cycle of hydrogen station technologies has progressed to the point where there exist more than 30 retail hydrogen stations in the California. It is now possible, in limited geographic regions like Southern California, to simply drive up to a local hydrogen station, pay, get fuel, and drive away. In the context of system engineering life cycle stages, nearly all of the hydrogen station systems are in the post-development stage. This post development stage for hydrogen stations includes constructing, deploying, operating, and maintaining phases. Table 2 provides a brief look back on hydrogen station development stages and looks at what the next stages will likely include.

Table 2. Systems engineering stages of U.S. based hydrogen infrastructure

Phase	Past hydrogen station development	Current and future hydrogen station development
Concept Development	<2006 • Need for hydrogen infrastructure driven by emissions reductions, domestic sourcing, and a vision of renewable generation • Station concepts include hydrogen production/delivery, compression, storage, and dispensing	2018 (current timing) - ~2020 • Next iteration of need for hydrogen stations grows in demand, location, variety, renewable requirements, and future transit solutions • New concepts in development
Engineering Development	2006 – 2015 • Hydrogen stations designed, built, and deployed through a DOE Learning Demonstration project • Station evaluation on-going for performance, safety, and maintenance, providing input to the next iteration of hydrogen station development in the concept stage • Primarily for light duty vehicles, some buses	~2020 - ~2025 • Advanced system and component design • System boundary may increase to include hydrogen sourcing, integration with other sectors (e.g., grid), station-to-X communications, autonomous operations • Multiple applications (e.g., cars, trucks, buses, and forklifts)
Post Development	2015 – 2017 (current timing) • Retail hydrogen sale starting around 2015 • Operation focused on availability and cost, providing input to the next iteration of hydrogen station development in the concept stage	~2030 • Construction and deployment of hydrogen stations and hydrogen dispensing at least an order of magnitude more than current levels

Based on these high-level observations, there exists a gap in the understanding of transportation hydrogen infrastructure and what is needed for a commercial market. We know that this infrastructure is small compared to those of other fuels, yet it is growing in both amount and the number of hydrogen fueling stations. However, based on this data, we do not know how these stations meet consumer expectations and requirements for expectations such as availability, reliability and cost.

Hydrogen station reliability directly impacts station availability and is one area where more research and information are needed to understand the topic. Reliability is important to our understanding of infrastructure because reliability influences consumer acceptance, costs, safety, and commercial success. Understanding station reliability requires data analysis on failures, maintenance, and demand for hydrogen fueling. Analysis of the performance of current hydrogen stations will identify existing reliability challenges and will set the research agenda for improving the economics and performance of hydrogen stations as the infrastructure and demand for hydrogen grows in the future.

CHAPTER 2 – RESEARCH QUESTIONS AND METHODS

2. Research Questions

Because hydrogen infrastructure for transportation has only recently advanced from the engineering development stage to an early commercialization phase, there is little published research literature on hydrogen station operation strategies and reliability, with the bulk of hydrogen station research literature focused on deployment strategies and long-term market scenario analyses. Based on this and technical research challenges outlined in Chapter 1, a primary research question can be posed:

Primary Research Question*: *Can a data-rich model of a hydrogen station system support the integration of predictive reliability engineering to address key technical challenges of availability and cost?

The primary research question is broken down into three research questions of smaller scope and the work required to answer each research question is broken down into tasks. Each task provides outputs which contribute to answering the primary research question and to accomplishing subsequent tasks.

2.1. Research Question 1 – What is the measured operational performance of current, consumer-oriented, retail hydrogen stations?

Previous research questions about hydrogen infrastructure sought to answer whether the technology would work under normative conditions, whether it was possible to do more than limited demonstration-type operation, and where and when stations should be deployed. Those questions have been answered through analysis and real-world evaluations primarily from the

DOE's technology validation program [62]. For this research, we can use current hydrogen station data to answer additional questions based on retail (instead of demonstration) operation. For example, 1) what are the gaps between actual performance with what was projected, 2) what are the gaps between actual performance and the station performance that would be required to meet future demand, 3) what is the current system readiness level, and 4) how can past data on performance successes and failures inform future designs and operational strategies. These questions are important to inform industry-specific stakeholders, measure progress, and educate a general audience about why hydrogen infrastructure technologies are relevant contributors to a sustainable mobility solution.

The first task for this research question is to complete an objective baseline assessment of FCEV and hydrogen infrastructure status and progress. This analysis relies on data from NREL's NFCTEC, where real-world data from both FCEVs and hydrogen infrastructure are stored, processed, and analyzed. These data include confidential and commercially sensitive data, which must be considered to enable an accurate technology evaluation. The second task is a gap analysis to understand the status of current hydrogen stations against their performance requirements. The gap analysis will look at near-term and long-term hydrogen station requirements such as cost and demand.

2.2. Research Question 2 – What are the sources of potential for station controls and operations optimization to improve the economics and effectiveness of hydrogen stations?

Real-world data on the operation and demand experienced by hydrogen stations has increased over the last decade and is at a point where data on real behaviors can drive optimized, data-based operation and maintenance (O&M) decisions. Time-varying demand for hydrogen impacts station availability and operation costs because demand can be variable and difficult to predict. This research question asserts that a station operation strategy that allows for the prediction of fueling demand can 1) schedule high cost operation (e.g., compression) at specific times to lower operating costs and not negatively impact customers, 2) participate in alternative revenue generating conditions (e.g., grid services), 3) optimize station component sizing, and 4) schedule downtime when there is the lowest risk of lost revenue and dissatisfied customers. The expected net effect of these improvements to hydrogen station operation will be an improvement in station economics (as measured by $/kg) and effectiveness (as measured by availability and reliability) that can be quantified explicitly.

The first task for this research question is to construct a dataset of driving and fueling behaviors from both FCEVs and hydrogen stations. These data will be mined for driving day, time, and distance as well as fueling day, time, and amount, to serve as the learning dataset for a near-term fueling demand scenario. Future demand scenarios will be constructed based on available data and forecasts. The second task is to build and verify a predictive fueling demand model from the fueling behavior database. The task requires the model to be flexible and capable of modeling under many different input variables. Scenarios will seek to model the number of FCEVs, other fuel cell vehicle types, and number of hydrogen stations deployed. Real-world station data provides the learning dataset for the model.

2.3. Research Question 3 – What strategies for active hydrogen station health monitoring are actionable and effective at improving hydrogen station reliability?

Hydrogen station availability and reliability is a leading concern because of its direct impact on FCEV drivers' satisfaction. Low station reliability results in dissatisfied customers, high costs, and unnecessary system complexity (e.g., redundancy, spare parts, and technician support), ultimately creating a station availability problem that can decrease consumer confidence. At present, the reliability of hydrogen stations is expected to not be high enough to meet the requirements of FCEV drivers. In 2018, the industry median "mean number of fills between failures" is less than 500, which results in frequent unscheduled maintenance activities. Another way to describe is this is in terms of technology readiness level [63], where the hydrogen system must be at a level of 9, a proven system, reliable in real-world operation.

There are many possible reasons for hydrogen stations' low reliability. One reason is from one-off failures that simply need a solution identified and implanted so those failures aren't seen again. Another reason is that hydrogen is a challenging fuel to manage in a consumer-oriented station system. Hydrogen's embrittlement properties and thermal/pressure operating conditions require complex systems to ensure user safety. Another reason is that the field of hydrogen station operation is early in a deployment/development cycle, and not enough of the reliability engineering best practices have been integrated into station O&M. The hypothesis associated with this research question is that the application of advanced reliability engineering methods like prognostic health management (PHM) for hydrogen station O&M will minimize unscheduled failures, thus increasing station availability.

The first task for this research question is the development of new metrics, datasets, and diagnostics to improve the reliability of hydrogen stations in practice. To date, hydrogen station evaluation projects have analyzed past events to study and report on station maintenance and reliability. This task will add to the existing research, with a framework that can be implemented and validated at hydrogen stations. The second task is to estimate the remaining useful life (RUL) for key subsystem and components. In addition, this task will estimate the benefits expected, specifically that the station O&M costs will decrease because 1) preventative maintenance will be informed by both best practices and current health estimates, 2) preventative maintenance will be scheduled to minimize impact hydrogen sale revenues, and 3) predictive fueling demand will enable controlled operation for additional revenue options like grid services.

CHAPTER 3 - REVIEW OF HYDROGEN STATION OPERATION, MAINTENANCE, AND DEMAND

3. Introduction to Hydrogen Station Performance

Quantifying the operational performance of current, consumer-oriented, retail hydrogen stations is the aim of the first research question. In order to answer this research question, an objective baseline assessment of fuel cell vehicle and hydrogen infrastructure was completed to provide the foundation of status and a benchmark for measuring gaps and progress. A gap analysis was also performed to understand the status against specific technical and economic criteria for successful hydrogen station operation. The gap analysis informs critical research needs that are necessary for the projected deployment of fuel cell vehicles and successful hydrogen station market.

This chapter reviews the engineering and practice of modern hydrogen infrastructure including the costs, benefits, operations (including safety, reliability, availability), and challenges to the scale-up of hydrogen infrastructure. The results of this review identify hydrogen station reliability as a key driver of hydrogen system operating expense. This chapter places hydrogen station reliability and its pathway forward within the context of the larger reliability engineering field.

3.1. Current Hydrogen Station Performance Status

The broad set of options for different hydrogen station designs, sources, and costs have largely converged to realize the retail hydrogen stations being installed today. At present, the state-of-the-art retail hydrogen station uses is functional and capable of meeting the relatively low demand of the current FCEV fleet. Numerous successful station demonstrations and their associated data sets have shown that disruptive advancements in the basic technology of hydrogen infrastructure are not needed for successful near-term hydrogen-fueled transportation, but that the operation of hydrogen stations must be improved to be able to move toward mass market hydrogen-fueled vehicles.

Because much of the hydrogen infrastructure that has been developed in the U.S. has been subsidized with public funding and is therefore subject to extensive data reporting [64], there is a relatively rich data set available for understanding the construction, operation, and economics of hydrogen fueling systems. Universities and national laboratories have published the operational characteristics of their single on-campus hydrogen stations [65], [66], [67]. Other relevant data sets document operating costs, operational uptime, and more [68], [69], [70]. The most extensive data set available to date that includes multiple stations and operators is at NREL's NFCTEC. The NFCTEC project collects hydrogen infrastructure operation, maintenance, and safety data for fuel cell systems and infrastructure [34], [71] from more than 10 project partners to a centralized site. The set of NFCTEC-reporting stations are the primary source of data for the operations-centric portion of this review.

3.1.1 FCEV Demand

With many thousands of FCEVs on the road, primarily in California in the hands of early technology adopters, the expectations of hydrogen infrastructure and the demand for hydrogen fueling can vary significantly as a function of time, and geography. New generations of FCEV technology have improved the vehicle's range while emphasizing the performance benefits. A decade long study of FCEV driving, fuel cell performance and durability, and vehicle range and fuel economy documented the significant progress in the technology (

Table 3). A recent FCEV evaluation included 42 vehicles with more than 2.3 million miles traveled and more than 72,000 fuel cell operation hours.

Table 3 summarizes the primary DOE targets and analysis results for four evaluation phases. The FCEV-specific data in Table 3 provides an insight into how the drivers fill their vehicles and their driving behavior between fills.

Table 3. Current Status against DOE 2020 Targets

Vehicle Performance Metrics	DOE Target (Year 2020)[a]	LD3[b]	LD2+[c]	LD2[c]	LD1[c]
Durability					
Max fuel cell durability projection (hours)	5,000	4,130	--	2,521	1,807
Average fuel cell durability projection (hours)		2,442	1,748	1,062	821
Max fuel cell operation (hours)		5,648	1,582	1,261	2,375
Efficiency					
Adjusted dyno range (miles) (window sticker)		200–320	--	196–254	103–190
Median on-road distance between fuelings (miles)		122 miles	98	81	56
Fuel economy (mi/kg) (window sticker)		52 (median)	--	43–58	42–57
Fuel cell efficiency at ¼ power	60%	57% (average)	--	53%–59% (max)	51%–58%
Fuel cell efficiency at full power		43% (average)	--	42%–53%	30%–54%
Specs					
Specific power (W/kg)	650	240–563	--	306–406	183–323
Power density (W/L)	850	278–619	--	300–400	300–400
Storage					
System gravimetric capacity (kg H2/kg system)	5.5%	2.5%–3.7%	--	--	2.5%–4.4%
System volumetric capacity (kg H2/L system)	0.04	0.018–0.054	--	--	0.017–0.025

[a] Fuel Cell Technologies Office Multi-Year Research, Development, and Demonstration Plan [1]

[b] Current results are available online [3] (updated May 2017) from Learning Demonstration 3 (LD3)

[c] National Fuel Cell Vehicle Learning Demonstration (LD) Final Report [2] which included two more phases Learning Demonstration 2 (LD2) and Learning Demonstration 2+ (LD2+) that had different generation vehicles and number of participating OEMs

3.1.2 Hydrogen Station Dispensing and Utilization

The quantity of hydrogen dispensed has increased significantly as hydrogen stations have moved from demonstration to retail and as FCEVs have moved from prototypes to commercial products.[1] As an example, among the stations in NFCTEC, less than 2,000 kg hydrogen was dispensed in all of 2009 while nearly 105,000 kg was dispensed from retail stations in 2016, and more than 913,000 kg was dispensed in 2018. Typical hydrogen stations being installed today are capable of dispensing 100–400 kg per day with typically one to two dispensers per station. Assuming typical values of 4 kg per fill and approximately 10 min per fill (includes time to connect, fuel, and drive away), a current station (capable of 200 kg per day, 90% availability) could complete fills for approximately 45 FCEVs spanning less than 8 hours of fueling per day.

The fill time is an important metric of station operation to understand the value proposition of hydrogen infrastructure and FCEVs relative to other technologies. A fill time of <5 minutes compares favorably with the fueling time of current gasoline technologies, or fast charge electric vehicle technologies. Hydrogen station dispensing pressure was increased to 70 MPa for light-duty vehicles around 2009 [8], and fueling protocols [72] for this higher pressure were developed at that time. From NFCTEC analysis of more than 35,000 fills, the average fill

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[1] All referenced NFCTEC data figures are available on NREL's website: https://www.nrel.gov/hydrogen/infrastructure-cdps-all.html

time for the most modern retail stations is 3.6 min, with an average fill amount of 2.9 kg. For just the 70 MPa fills, the average fill rate is 0.84 kg/min and the average fill amount is 3.1 kg per fill.

Daily hydrogen station utilization is defined as the ratio of daily hydrogen dispensed to the daily station nameplate capacity (which includes estimates of throughput and maintenance). Actual daily usage may exceed a station's nameplate capacity, as that capacity is not necessarily a physical limit and is not defined uniformly across all stations. High hydrogen station utilization is an important indicator of the economic viability of the hydrogen stations, and lower utilization indicates the capacity to serve more vehicles. Early hydrogen stations were deployed so as to achieve geospatial coverage of a region, as opposed to high utilization [52]. There has been a large variation in fills from quarter to quarter and station to station, as well as times with low utilization, which indicates a capacity for more fills. The average daily utilization of the average individual hydrogen station is currently ~35%, which is lower than what would be required for to maximize the economic return on investment. Hydrogen station utilization is expected to increase as more FCEVs are deployed. Overall the utilization trend is increasing and some stations have seen a large increase in utilization rate (which is proportional to dispensing rate, see Figure 7), averaging 50–100 kg/day or 10–30 fills/day.

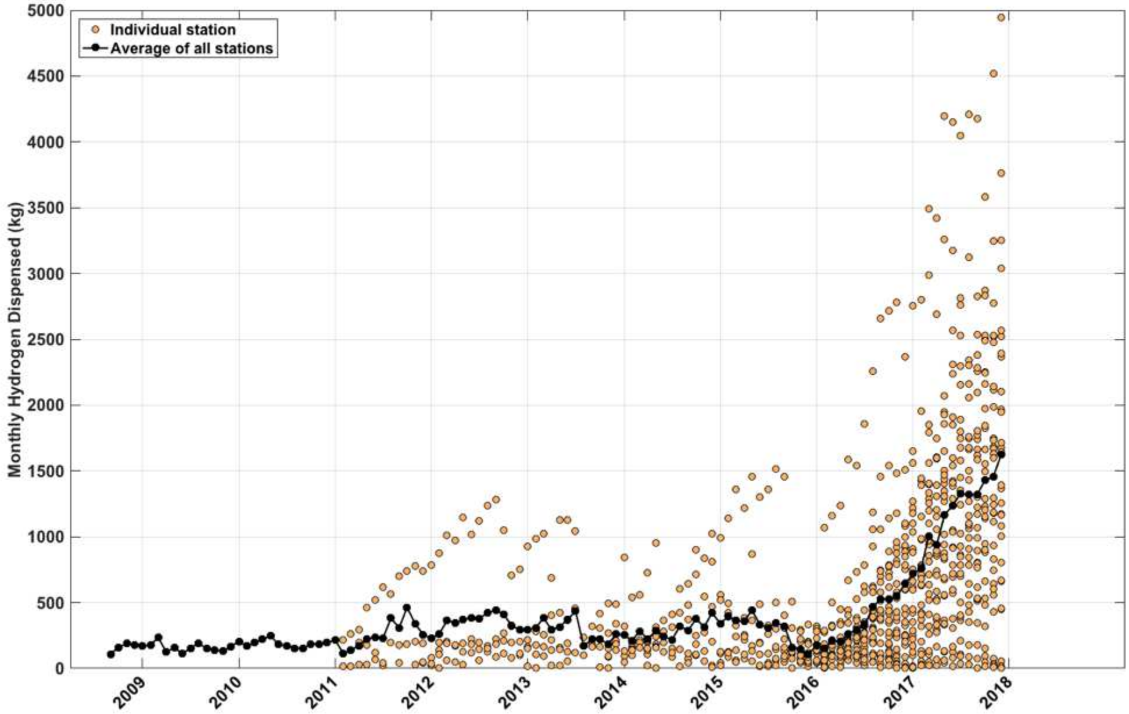

Figure 7. Hydrogen dispensed by month and by station for NFCTEC stations

3.1.3 Hydrogen Station Operation Costs

To maximize revenue from hydrogen sales, the capital costs along with O&M costs must be minimized. At present, current prices (Figure 8) at the pump for 70 MPa hydrogen are between \$10/gge (gasoline gallon equivalent, where the energy of one kilogram of hydrogen is approximately equivalent to the energy of one gallon of gasoline) and \$16/gge [73], [74]. This is significantly higher than the price that is required for cost competitiveness with conventional fuels (\$3/gge to \$5/gge).

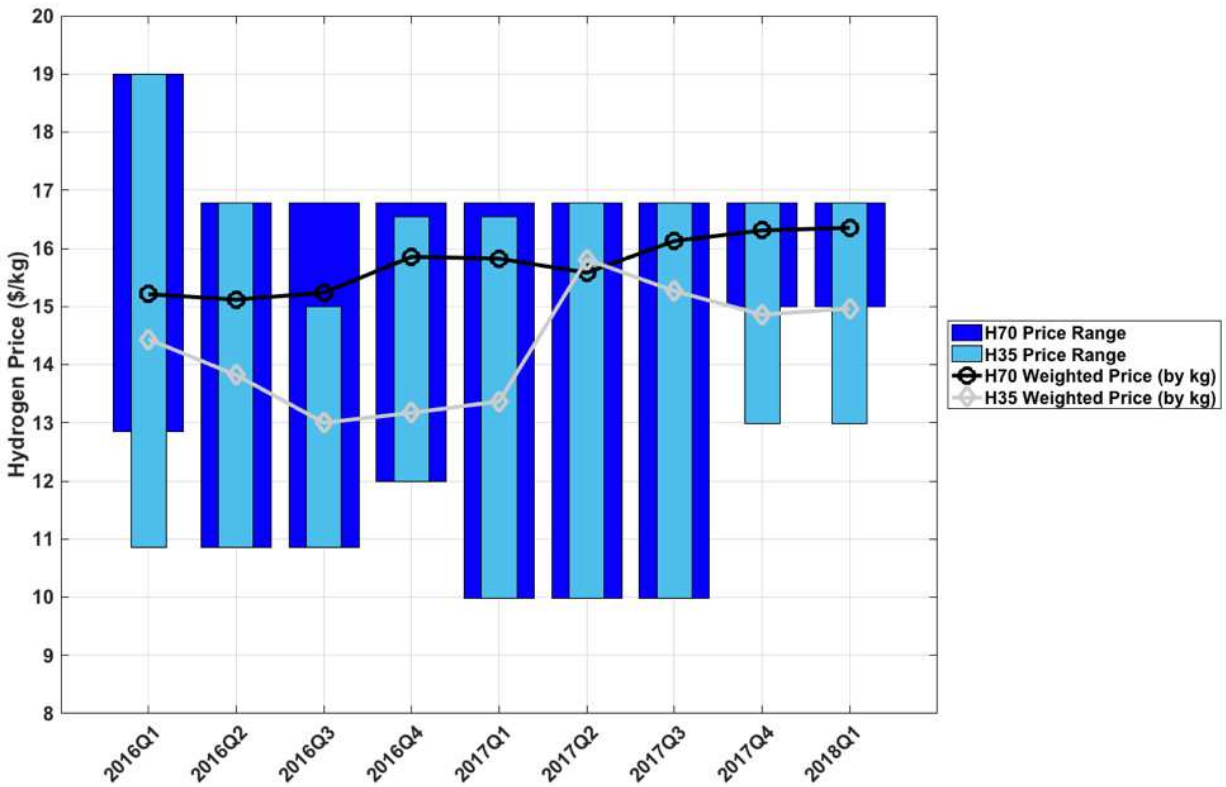

Figure 8. Hydrogen price over 2016 and 2017

Numerous studies have concluded that cost competitive hydrogen is possible today using low-cost production methods and high station utilization [75], [76], [77], [78], [79], [80], [81]. These studies indicate that the primary driver for low-cost hydrogen is the economies of scale that are available to achieve lower capital costs with large stations operating at a high hydrogen dispensing rate. At an average throughput of 750–1,000 kg of hydrogen per day, the costs of delivered hydrogen can be cost competitive because the capital cost of the hydrogen infrastructure can be reduced per kilogram of hydrogen delivered. This rate is much higher than the dispensing rate (<400 kg/day capability and <100 kg/day in practice [34]) of current stations. Uncertain demand can also present hydrogen stations with cost challenges. An example of this can be found in a study of hydrogen station deployment in New Jersey, which does not have a strong demand already in place [82]. The researchers studied the hydrogen station supply chain based on size, location, and demand scenarios, including the process from hydrogen production to dispensing. The results provided recommended type, size, and location for stations (e.g., steam methane reformed hydrogen supporting three stations in the first 5–10 years) to minimize the economic risk due to uncertainty in hydrogen demand.

3.1.4 Hydrogen Station Safety

Safe operation is essential for successful deployment and operation of hydrogen stations. A guiding safety code is the National Fire Protection Association (NFPA) 2 Hydrogen Technologies Code. The NFPA 2 code "provides fundamental safeguards for the generation, installation, storage, piping, use, and handling of hydrogen in compressed gas form or cryogenic liquid form" [83]. A quantitative risk assessment informs hydrogen station permitting and can be useful for evaluating compliance with code requirements [84]. Traditional fault and events trees [85] and Bayesian Networks have been studied for hydrogen station risk modeling. Risk analysis and hazard identification are critical steps to inform the codes and safety requirements in a reliable and cost-effective manner for many different hydrogen station scenarios. For example, a hazard analysis for a hybrid gasoline-hydrogen fueling station in Japan identified 314 scenarios (e.g., leaks and collisions) that should be mitigated for this particular system with its unique considerations [86].

During station operation, the safety is monitored through tracking alarm data sets and safety-related records in the station maintenance logs. These safety reports, per the NFCTEC data (Table 4), are classified by a severity category: minor hydrogen leak, near-miss, or incident. A "near-miss" is an event that could have become an incident and an "incident" is an event that results in injury, damage, or impact to the public or environment. To date, the hydrogen station safety record is excellent. As might be expected, minor hydrogen leaks correlate with the commissioning of new stations; no single subsystem dominates these incidents; and the hydrogen leaks are generally minor, without accumulation.

Table 4. Summary of safety reports and station count by year

Safety Reports	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
Station Count	3	4	5	11	30	36
Incidents	0	0	0	0	0	1
Near Miss	1	1	1	1	3	6
Minor Hydrogen Leak	16	7	16	4	19	7

3.1.5 Hydrogen Station Reliability

Hydrogen station availability and reliability is a leading concern raised from the perspective of the FCEV manufacturers because of its direct impact on the FCEV customer experience. Low station reliability results in high maintenance costs, lowered revenues, system complexity, low availability, and dissatisfied customers. NFCTEC publishes the only regular studies of the reliability of retail hydrogen stations based on maintenance data supplied from station operators. These data include date, system, type, labor time, cost, and description. The NFCTEC analysis is separated into maintenance analysis and reliability analysis. The maintenance results focus on the categorization of maintenance events, and aggregated maintenance statistics, such as percentage of maintenance events that were unscheduled. The reliability analyses focus on characterizing those maintenance events against time, such as mean fills between failures (MFBF). The four most common equipment categories for maintenance events are compressors, dispensers, entire system, and chiller systems. These subsystems and their interfaces may be particularly amenable to reliability improvement strategies.

The hydrogen stations reliability data are also categorized into scheduled issues, and unscheduled issues. Maintenance data is collected from operational stations via maintenance logs and submitted to NFCTEC, which is used to analyze station reliability. NFCTEC maintenance data for retail hydrogen stations includes more than 5,600 maintenance events, and more than 14,700 hours of labor, with 69% of those events being unscheduled maintenance. The leading equipment categories for maintenance are dispenser and compressor. For an analysis of the MFBF, the station is separated into sub-systems. The sub-systems are the:

- Air management
- Thermal management
- Electrical
- Safety
- Gas management panel (used for mechanical control)
- Storage
- Chiller
- Dispenser
- Compressor

There are three other categories (entire, station other, and summary) which are specified by the data providers for events that are not easily categorized by either the sub-system.

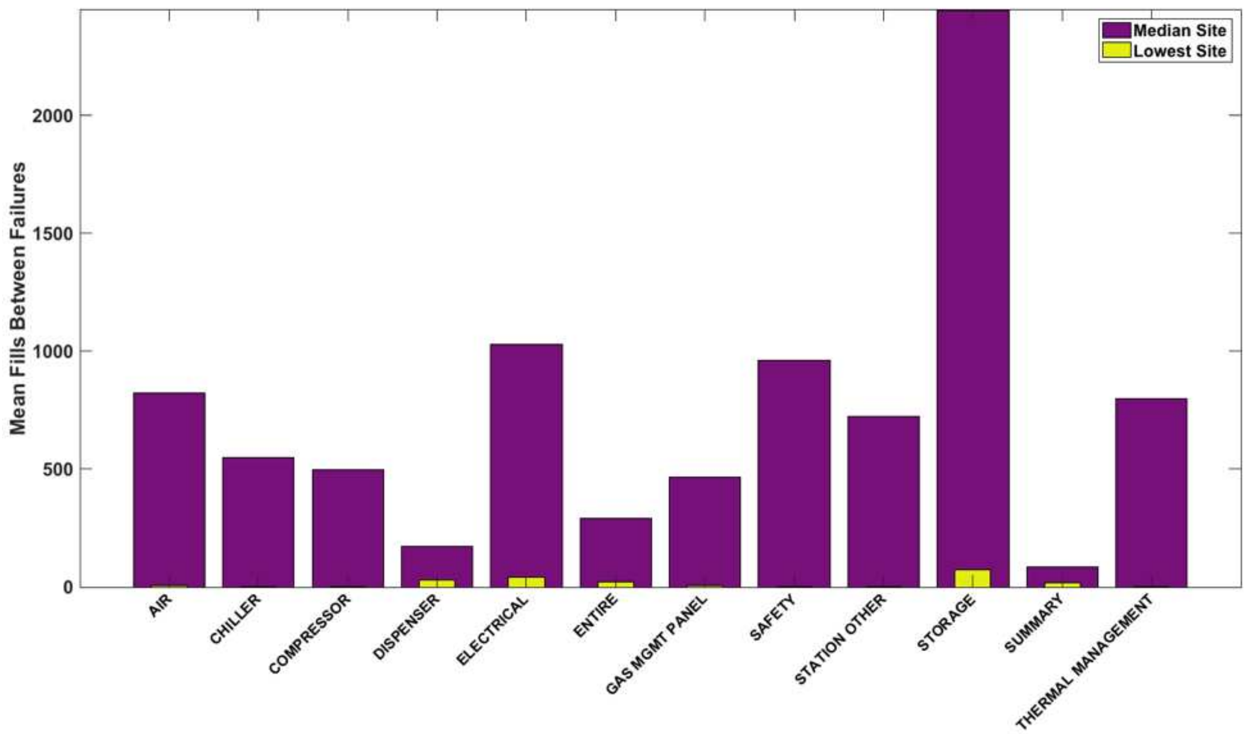

Figure 9. MFBF by equipment category

Limiting the analysis to only the latest retail stations so as to remove aging stations, there are five different subsystems that have an MFBF of approximately 500 fills or less. These categories include compressors and dispensers, the two leading maintenance equipment categories. In 2017, the dispenser category had an MFBF of less than 250, which leads to high levels of unscheduled maintenance activities (Figure 9). It appears that the reliability of hydrogen stations is not high enough to meet the requirements of FCEV customers since a station MFBF will not be better than the poorest subsystem MFBF and many subsystems have a MFBF of less than 500.

3.2. Addressing Station Operation Challenges with Reliability Improvements

This review of publicly available data has identified a set of near-term challenges, specifically reliability, throughput, and O&M cost. Low reliability presents a barrier to economically viable hydrogen infrastructure because it not only increases the maintenance cost contribution to the pump price but also decreases availability and the amount of hydrogen dispensed. By addressing reliability issues, the industry should enable improvements to throughput and lower maintenance costs, and thereby to the cost to dispense retail hydrogen.

3.2.1 Reliability as a Primary Research and Development Challenge

The station O&M data show that reliability and throughput are significant contributors to the price of hydrogen per kilogram, which is currently about 4 times the gasoline price. O&M cost contributions represents periodic costs (e.g., initial failures, end-of-life failures, and learning failures) as well as costs due to a persistent reliability issue. On average, stations have less than 500 fills between failures for critical subsystems like compressors, dispensers, safety, and chillers, and more than 50% of all recorded maintenance hours are for unscheduled events. Although station monthly availability values may be greater than 90%, the unsteady nature of station demand means that the station may be unavailable (due to unscheduled maintenance) during periods of high demand and high potential revenue.

Figure 10 illustrates a possible cost reduction pathway based on improving reliability. Benefits of improving reliability are:

- Decreased cost to maintain the station,
- Increased revenues due to increasing the time that the station is available because of proactive instead of unscheduled maintenance practices
- Mitigated failures improve next-generation component and subsystem technologies.

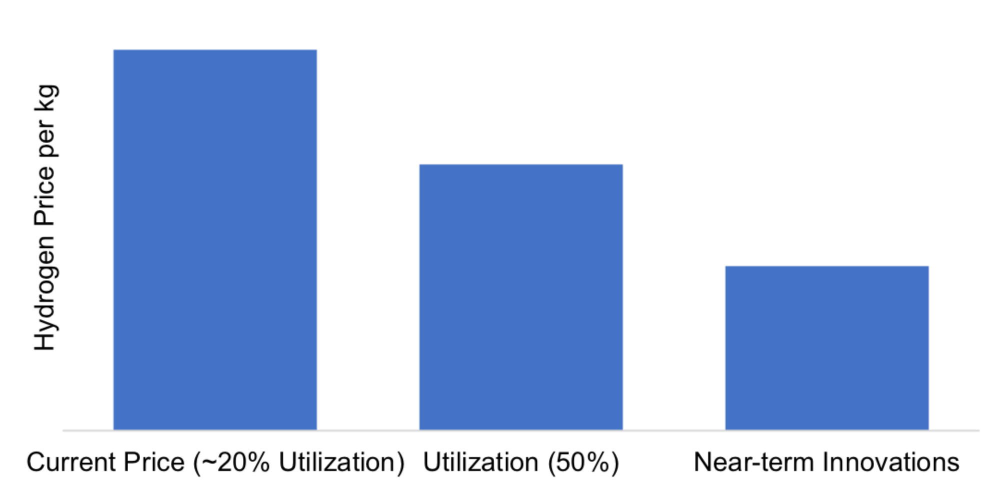

Figure 10. Conceptual cost reduction pathway due to reliability improvements and technological innovations

3.2.2 Reliability Engineering for Hydrogen Stations

Generally speaking, availability and reliability are closely related. For example, if a station is unable to complete a successful fill when requested, unscheduled maintenance will likely be triggered resulting in station downtime and lower availability. This section presents a high-level definition of availability and reliability in the context of hydrogen stations.

Hydrogen station availability is defined as the fraction of the time over which the station is able to fuel a vehicle when requested. The station operational availability (Equation 1) is defined as

$$A_o = \frac{Uptime}{Operation\ Period} \tag{1}$$

The operation period is daily hours and weekdays that the retail station is open for fueling and station uptime is the collection of time the station is online [87]. The operation period for a station excludes preventative maintenance time. For example, a station that is capable of 24/7 operations, and had 14 hours of downtime to repair an unscheduled compressor failure in May, has an availability of 98% in that month. Even with a relatively high monthly availability of

98%, the costs associated with 98% unavailability may be high, as the unavailable times may occur during a high use time of the month. Connecting station availability with station operation strategies becomes important, because there will be periods of time when the economic impact of an unavailable station is higher than other times.

One measure of reliability is if the station can complete a full fill that is requested. The station reliability (Equation 2) is defined as

$$R = 1 - \frac{Unsuccessful\ Fills}{Attempted\ Fills} \tag{2}$$

For example, a station with 5 unsuccessful fills over a period when 100 fills where attempted has a reliability of 95%. An unsuccessful fill is defined as any attempted fill that did not end with over 95% of the storage capacity.

Reliability is a focus for the remainder of the research because there is an opportunity to apply best reliability engineering practices to improve station reliability, which in turn should improve both station operation cost and availability.

The reliability engineering literature describes a number of ways to improve the reliability and ultimately the availability of complicated systems, many of which have not been applied to hydrogen system infrastructure. One way to systematically improve the system is to improve the reliability of the subsystem or component with the poorest reliability. This method involves developing a reliability engineering project or program for individual component(s) or subsystem(s). The U.S. Army Material Systems Analysis Activity published an AMSAA Reliability Growth Guide [88] that summarized the benefits of reliability growth management to be finding unforeseen deficiencies, designing improvements, reducing risk, and increasing the probability of meeting objectives. These methods, aimed at improving reliability and decreasing unforeseen failures, have been developed and are applied in many different industries and include considerations for cost [89]. Rotating equipment is a common application for reliability engineering [90], [91], and the wind industry is applying diagnostics and prognostics to improve wind farm reliability [92], [93]. Application of these methods with retail hydrogen stations is new and there are little to no published results on using advanced reliability engineering tools to improve hydrogen station availability.

In addition to reliability improvement programs, conducting system-level active monitoring and diagnostics to determine station health, as well as prognostics may have the potential to improve hydrogen infrastructure reliability. This assertion is based on best practices from other industries that have made reliability improvements from implementation of prognostics and health management (PHM) [94], as well as the application to new technologies like unmanned aerial vehicles [95]. PHM allows for the dynamic processing of information to predict failures before the failures happen, which can be used to drive optimal O&M strategies. The potential to actively integrate maintenance operations into times of the day or times of the week that experience low-demand for fueling services could improve the cost and availability of hydrogen infrastructure.

3.3. Conclusions

Hydrogen infrastructure for fueling light-duty passenger vehicles has moved beyond an idea to a reality and is operating in a conventional retail manner, with simple access and sale. Hydrogen stations are operating in a 24-hour, 7 day a week retail environment, satisfying the basic consumer needs of dispensing hydrogen quickly and safely. Through analysis of the current station performance of hydrogen stations in California, this chapter has demonstrated that FCEV drivers can fill with much of the same ease and convenience of a gasoline vehicle, although there exists some market limitations such as higher fueling costs, low numbers of hydrogen stations in

California, and problems with station availability and reliability. As an example of the infant market stage there are approximately 6,000 FCEVs in California, which has millions of gasoline vehicles. California has 35 hydrogen stations and over 8,000 gasoline stations. Hydrogen dispensed prices range from $12-$16/kg, which exceeds the typical gasoline price of $3-$5/gallon. A hydrogen station dispenses approximately 100 kg per day on average, which is significantly smaller than the daily average gasoline dispensed amounts of around 4,200 gallons.

FCEV customers rely on the hydrogen infrastructure now to meet their transportation needs, and they require hydrogen stations with low cost, high reliability, and high availability. Only by meeting these metrics of customer satisfaction and commercial viability will hydrogen infrastructure be able to grow to meet the economic and sustainability goals of hydrogen-fueled transportation.

Various stakeholders have been studying retail hydrogen station development, renewable hydrogen production, and innovative hydrogen station components and operation strategies through both analysis and hardware experiments to enable commercial viability for hydrogen-fueled transportation. Industry (e.g., industrial gas suppliers, oil and gas companies, and small station operation businesses), agencies like the CEC and California Air Resources Board, and research organizations have supported hydrogen station advances as evident in the rapidly increasing station utilization and demand in the 2 years. This has revealed other technical challenges like include how to accommodate increasing demand while decreasing costs and improving station availability and reliability.

Based on this analysis, the hydrogen station system has not yet achieved preferred operation capability in all key areas, especially cost and reliability where maintenance costs along exceed the price per kilogram dispensed hydrogen. Overall four gaps (capital costs, reliability, multi-use (e.g., truck fills), and cost-effective renewable hydrogen) were observed as challenges for economically viable hydrogen stations. Reliability is a specific technical gap that is largely unaddressed by the active hydrogen research community and is identified in this analysis as an area where improvements can realize significant economic and consumer acceptability benefits.

A systems engineering approach to improve hydrogen station reliability points some of the tools of reliability engineering that could be applied to hydrogen stations for economic benefits and improved reliability. For instance, the application of PHM, is used by many industries because of its proven ability to improve operation strategies, reliability, and costs. While there is an abundance of published literature on PHM, there is little to no research and published results on hydrogen stations implementing PHM. Based on the PHM literature and realizing that this is may be an ideal application to hydrogen stations, the application of PHM to hydrogen stations should improve (i.e., decrease) the operating and maintenance costs by predicting the health of the system and its components so that costly (parts, labor, and lost fueling revenue) unscheduled failures will be minimized.

This review indicates that a comprehensive PHM could be a key component of improving the commercial potential of hydrogen fueling stations, especially when demand is factored into the O&M strategies. Improved hydrogen station O&M is expected through a continuous, real-time assessment of subsystems and components so that maintenance can be planned for optimal times and to identify the highest priority components that need dedicated reliability improvements based on frequency, severity, and cost for repair/replacement. More detail is needed on the status of hydrogen station to develop and integrate a PHM with hydrogen station operation. Therefore the next chapter of this work studies hydrogen station reliability and proposed methods to evaluate the benefit for station O&M.

CHAPTER 4 – RETAIL HYDROGEN STATION RELIABILITY STATUS AND ADVANCES

4. Introduction to Hydrogen Station Reliability

Hydrogen station component reliability varies station-to-station and subsystem-to-subsystem, as observed in Chapter 3. All hydrogen stations generally have the same basic functions of storage, compression, and dispensing managed with system controls and safety. However, the details of the hardware and software to achieve those functions can vary significantly between stations, which can account for some variation in reliability. For example, the hydrogen source may be delivered gas, delivered liquid, pipeline, on-site generation via electrolysis, or on-site generation via reformation. Additional station design and operation variety includes component selection and sizing, station capacity, fueling positions, and fill method. These station configuration differences, along with different station operators and station ages, present a challenge in interpreting and utilizing the maintenance data as has been published to date. This study seeks to further characterize the relevant reliability information that can be gathered from an analysis of real-world station O&M data, leveraging the basic functions and protocols that are shared for all stations.

This study uses extensive datasets of the operation, safety, and maintenance of both hydrogen stations and fuel cell electric vehicles. The reliability analysis, described in this chapter, quantifies the current state and the challenge of hydrogen station reliability. In 2018, the industry median "mean number of fills between failures" (MFBF) was less than 500, with correspondingly high levels of unscheduled maintenance activities. By connecting the records of these failures with those of over 5,000 maintenance events, this work presents the categories and maintenance reasonings that are the prerequisites to a deeper understanding of system failures and industry-wide data-driven reliability improvement plans.

4.1. The System of a Hydrogen Station

Hydrogen can be a key enabler for U.S. energy goals such as affordability, reliability, sustainability, and security as described in the U.S. Department of Energy's (DOE) Hydrogen at Scale (H2@Scale) research [1]. Embedded in the H2@Scale system of systems concept is the infrastructure to enable robust connections between the generation and consumption of hydrogen. Hydrogen infrastructure is presently used to support many applications such as fuel cell transportation (like forklifts, cars, buses, and trucks), stationary power (e.g., baseload distributed heat and power, peak shaving, and backup power), and industrial processes (e.g., ammonia, petroleum refining, and paper processing). To meet these needs, the United States produces approximately 10 million metric tons of hydrogen a year [17]. For the purpose of this dissertation, the focus is on a key and growing subset of the H2@Scale vision hydrogen stations for light-duty passenger fuel cell electric vehicles (FCEVs).

An FCEV has many of the same consumer-preference attributes (fast fueling time, range, mass, and size) as today's conventionally fueled vehicles. The infrastructure necessary to supply hydrogen to the FCEV provides production and delivery to the station (or production at the station), storage, compression, and dispensing. These systems are collectively referred to as a hydrogen station for the purposes of this paper. Hydrogen stations must have many of the same consumer-preference attributes as conventional (gasoline) fueling stations (e.g., location, 24/7 operation, and accessibility). Technically, the goal of a station is to safely transfer hydrogen fuel into a vehicle's storage system while meeting time, pressure, and temperature requirements. These activities must be performed with high reliability, while minimizing maintenance costs.

The numbers of hydrogen stations are growing as their importance in supporting public FCEV fleets increases. There are currently 35 retail hydrogen stations operational in California, the region with the highest U.S. deployment of hydrogen stations and FCEVs [47]. More than 6,000 FCEVs, which have been bought or leased through automobile dealers, are on US roads. Hyundai, Toyota, and Honda all offer FCEVs for purchase and/or lease [22]. In their early demonstration stages (prior to 2015) most hydrogen stations were private stations, not for retail, and had restrictions on users, training, and hours of operation. There were fewer than 10 U.S. retail hydrogen stations prior to 2016 [34], and in less than 2 years the number of retail hydrogen stations has climbed to 39[2]. The majority of stations have hydrogen delivered to the station, and fewer than 5 have on-site hydrogen production. In California alone, the number of hydrogen stations is expected to exceed 60 within 2 years [96]. The California Fuel Cell Partnership released a vision for 1,000 hydrogen stations supporting 1,000,000 FCEVs in California by 2030 [97]. This vision addresses near-term deployment strategies that are focused on coverage and high-density urban areas, then moving towards a self-sustained market for hydrogen stations and FCEVs. In a report reviewing deployment options for the Northeast US [98], 50 hydrogen stations are projected to be operational in the region by 2022. Another future deployment study considered two scenarios for hydrogen station deployment [99]. One scenario with only limited FCEV adoption in populated urban areas and the second scenario with widespread FCEV adoption across the U.S. The urban area analysis, used to understand requirements and not to

[2] Refer to the Alternative Fuels Data Center (afdc.energy.org) for the latest station count (and planned stations) as the number of stations changes frequently

project FCEV deployment, suggests a need for 105 stations in 2020 and over 700 stations in 2030 dispensing approximately 300 kg/day and 550 kg/day respectively.

In order to safely dispense hydrogen to a FCEV, a hydrogen station typically has those major subsystems identified in Figure 11 [100]. The hydrogen source identifies where the hydrogen comes from for the station. For example, delivered hydrogen (either gas or liquid) is produced away from the station and brought to the station via truck or pipeline. The source, along with how the hydrogen will be dispensed and estimated capacity, determines the size and type of station storage. Dispensed hydrogen gas is compressed by the compression subsystem to either 35 MPa or 70 MPa, depending on the vehicle type. Hydrogen station dispensing pressure was increased to 70 MPa from 35 MPa for light-duty vehicles around 2009 [8], and fueling protocols [72] for this higher pressure were developed at that time. The 70 MPa fueling protocol require a hydrogen dispensing temperature of -40^{o}C to enable safe and fast fueling without overheat the on-board vehicle storage tank(s). The chiller subsystem performs fuel cooling immediately before dispensing to the vehicle. The user interface, and station-to-vehicle interface are typically contained within the dispenser subsystem. An overall management subsystem and safety subsystem interface with all aspects of the station equipment and control.

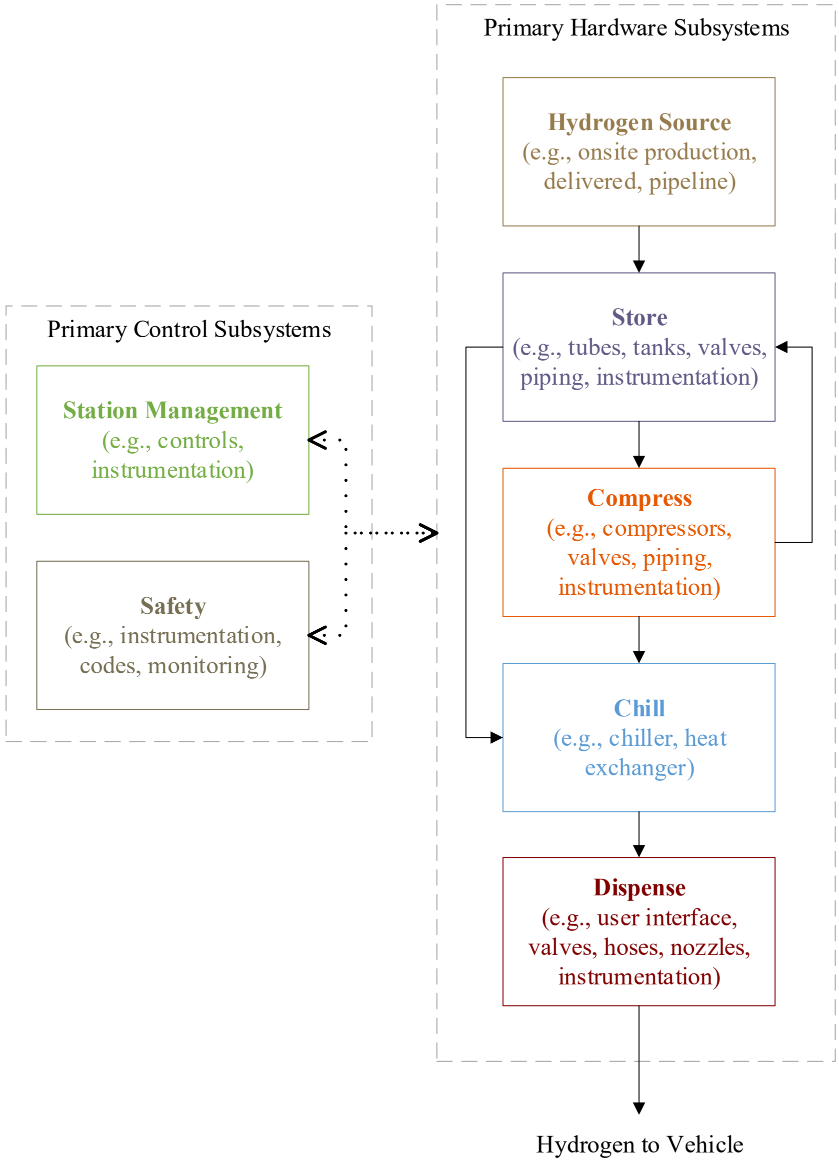

Figure 11. Generic hydrogen station block diagram (color code corresponds to subsystems in Figure 12)

With over 6,000 FCEVs on the road, the demand for hydrogen is high enough that some current stations have a high utilization percentage (>80%) [101]. Projections [96], [48], [102], [68], [103] indicate that the number of FCEVs is expected to continue to increase, with more and bigger hydrogen stations needed to fuel the FCEVs as well as trucks and buses [104], [105]. One anecdotal concern for FCEV drivers, as detailed in a consumer survey [106], is hydrogen station availability, which is directly connected with station reliability. In order to more completely characterize reliability, this chapter describes an analysis of hydrogen station maintenance data, and a reliability growth analysis using field data from hydrogen stations and an understanding of the hydrogen fueling market.

This chapter is organized as follows. The overview of the data and reliability analysis methods is covered in Section 2. The reliability of current hydrogen stations is provided in Section 3. Section 4 reviews on-going research into the failures of hydrogen dispenser components that can improve hydrogen station reliability with conclusions covered in Section 5. This work is novel in that it uses a consistent reliability analysis method to provide a status of hydrogen station reliability as a benchmark to track progress and needed improvements. This research originates from a unique dataset of multiple hydrogen stations operating under real-world conditions. This work also connects the current reliability status, where dispensers are the leading subsystem requiring maintenance, with dispenser component failure research that is expected to improve station reliability.

4.2. Hydrogen Station Datasets and Analysis Methods

4.2.1 NFCTEC Datasets and Methods

Researchers at NREL's NFCTEC, supported by DOE's Fuel Cell Technologies Office, have studied the operation, maintenance, and safety of hydrogen stations and FCEVs for nearly 15 years [34], [8], [107]. In order to understand the current status and gaps for hydrogen station reliability, this study mines the NFCTEC datasets that are communicated from the hydrogen stations and their operators. The NFCTEC collects hydrogen infrastructure data from more than 10 project partners to a centralized site. Project partners report operation, performance, maintenance, station cost, and safety data for fuel cell system(s) and infrastructure. This data is received at least quarterly and is then processed, stored, analyzed, and aggregated. An internal analysis of all available data is completed quarterly and a set of technical composite data products (CDPs) is published every 6–12 months.

To inform stakeholders, data-driven results are uploaded to NREL's technology validation website [107] and presented at industry-relevant conferences. The CDPs present aggregated analysis results across multiple systems, sites, and teams in order to protect proprietary data and summarize the performance of hundreds of fuel cell systems and thousands of data records. A review cycle is completed with the data partners before the CDPs are published. This review cycle includes providing detailed data products of individual system- and site-performance results to the specific data provider. Detailed data products also identify the individual contribution to the CDPs. Analyses are created for general performance studies as well as for application- or technology-specific studies. By working closely with the data providers, the quality and validity of the dataset can be continuously assessed and improved.

The hydrogen station operators report to NFCTEC using data templates (the maintenance data template is shown in Table 5). All of the NFCTEC maintenance and reliaiblity analyses use data from the maintenance template, which includes one row entry for each maintenance event. The date, component, subsystem, action, cause, effect, downtime, category, labor time, and costs are recorded and reported. For this study, we use both the NFCTEC maintenance log from each station, and the NFCTEC log of hydrogen filling events data that includes fill date/time and fill amount. Both of these data sources are available for every station. The data is analyzed and aggregated to benchmark station performance and maintenance events and to inform research needs to improve the reliability of hydrogen station subsystems and components.

Table 5. Sample NFCTEC maintenance data template

Maintenance Template	*Example Entry*
Site	Station A
Date of Repair/Replacement	10/5/16
Component Name	Dispenser Nozzle
Subsystem	Dispenser
Component	Nozzle
Action	Replace
Cause	Material Fatigue
Effect	Functionality Lost
Station Unavailable (hours)	8
If still available, station performance affected (hours)	0

The NFCTEC maintenance data is then parsed into categories of maintenance data and reliability data. The maintenance data focus on maintenance categories and aggregated statistics, such as percentage of maintenance events that were unscheduled. Tracking of hydrogen leaks is included in the maintenance dataset because it has proven relevant to investigations into hydrogen leak frequency and quantitative risk assessment tools such as the Hydrogen Risk Assessment Model [84]. The reliability data focuses on characterizing maintenance and failure events as a function time, including metrics such as MFBF. The fill event data includes over 183,000 fills from 29 stations with over 4,600 maintenance events from 2015 to 2017.

4.2.2 Reliability Analysis Methods

This study presents a reliability analysis based first on an analysis and categorization of the types of failure modes and maintenance events that were recorded in the NFCTEC datasets. Each type of failure and maintenance event is allocated to a subsystem, cause, effect, operation mode, and more. These analysis results are presented to communicate the types of failures that these hydrogen stations encounter, their frequencies and subsystems that are particularly failure prone.

The second set of results use the Crow-AMSAA reliability growth model [108], [109], [110] to more quantitatively understand the dynamics of hydrogen station system failure. Although other methods of analysis were considered (e.g., Weibull [111], [112], [113], [114], failure modes and effects [115], physics of failure, and fault tree analyses), for a few reasons, the fundamental Crow-AMSAA model was found to be most effective and applicable for analysis of the NFCTEC dataset. First, the NFCTEC data can be characterized as dirty data in that it is not specifically controlled for reliability analysis and it may be incomplete with mixed failure modes. Second, this analysis considers each hydrogen station to be a repairable/maintainable system [116], so that the Crow-AMSAA modeling can be used to track reliability growth and predict failure modes and forecasting of future failures. Finally, the Crow-AMSAA model can also be used to evaluate the success of a reliability improvement plan by studying the rate of failures before and after improvements.

The instantaneous failure rate Crow-AMSAA equation is:

$$\rho(t) = \lambda\beta t^{\beta-1} \tag{3}$$

where $\rho(t)$ is the rate of occurrence, λ is the scale parameter, β is the shape parameter, and t is the aging parameter (often time but it may be fills or dispensed hydrogen amount for candidate hydrogen station reliability models). A shape parameter that is greater than one indicates an increasing failure rate and less than one indicates a decreasing failure rate. This instantaneous failure rate is the first derivative of cumulative events:

$$n(t) = \lambda t^{\beta} \tag{4}$$

where $n(t)$ is the cumulative failure events. The reciprocal of the instantaneous failure rate is the mean time between failure (MTBF):

$$MTBF = \frac{1}{\rho(t)} \tag{5}$$

This type of Crow-AMSAA model is applied to each station, subsystem, and key component for all available NFCTEC datasets.

4.3. Current Status of Hydrogen Station Reliability

Results of the categorization of each of the failures and maintenance events in the NFCTEC dataset is presented in this section. No differentiation among the stations is made for these results.

4.3.1 Analysis of Hydrogen Station Maintenance Data

Each of the hydrogen station maintenance events are allocated to categories (allocation to systems, subsystems, etc.), and maintenance types (scheduled or unscheduled). The analyzed maintenance data through 2017 included 4,663 maintenance events, 69% of which were unscheduled. Maintenance events for the major station subsystem and component categories (dispenser, compressor, and chiller) account for 78% of the events (Figure 12). A miscellaneous category captures 14% of the maintenance events and includes subsystems such as feedwater, electrolyzer, thermal management, storage, safety, gas management, air, electrical, and other. The events are categorized based on the station operator-supplied categories and are aggregated among all the stations providing data.

The results of this categorization are shown in Figure 12. The largest fraction (46%) of maintenance events (planned and unplanned) and maintenance hours are associated with the dispenser subsystem. This subsystem includes various components that have relatively high rates of failure including the flexible hoses, dispensing valves, and user interfaces. On the other hand, unclassified station events make up a disproportionate fraction of the maintenance hours, and therefore maintenance costs. Several failures (~930) were recorded as allocated to the station as a whole (identified as "Station System"), which are primarily scheduled maintenance events like preventative maintenance, and upgrades. The "Station System" or "Entire" category is for any feature or detail that station operators and technicians categorize as encompassing multiple subsystems such as overall station controls and interfaces. There is also large number of maintenance hours allocated to this system's repair in the "Station Other Subsystems" category. This is representative of maintenance events that may require more time to identify and fix. The "station other" category represents general station electrical, gas management, storage, on-site production, and thermal management systems which can be high hour maintenance events. This breakdown of events and maintenance hours provides a benchmark to inform hydrogen station stakeholders of the leading maintenance categories.

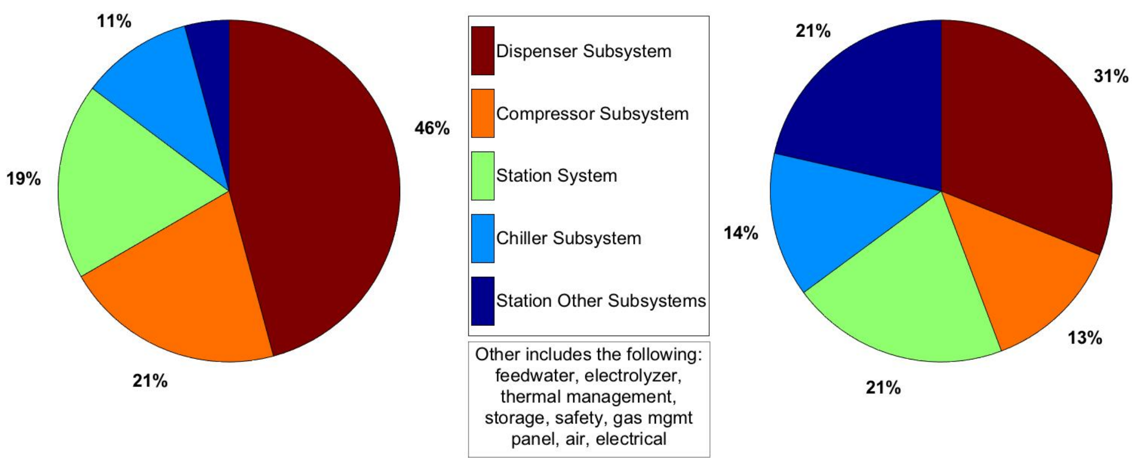

Figure 12. Maintenance events and maintenance hours by equipment type for NFCTEC retail stations

Expanding on the results of this benchmark, we studied unscheduled maintenance events associated with particular failure modes, as shown in Figure 13. In the case of the dispenser subsystem, the failure modes can be categorized as either communication-related, undetermined, miscellaneous, or scheduled. Of the recorded dispenser maintenance events, 18% are scheduled maintenance and more than 75% are the undetermined/miscellaneous failure mode, indicating that many of the failure modes are failures, leading to unplanned maintenance. As comparison, the compressor subsystem has significantly less frequent maintenance events than the dispenser category does, but it has a higher fraction of undetermined or miscellaneous (i.e. unplanned) maintenance events.

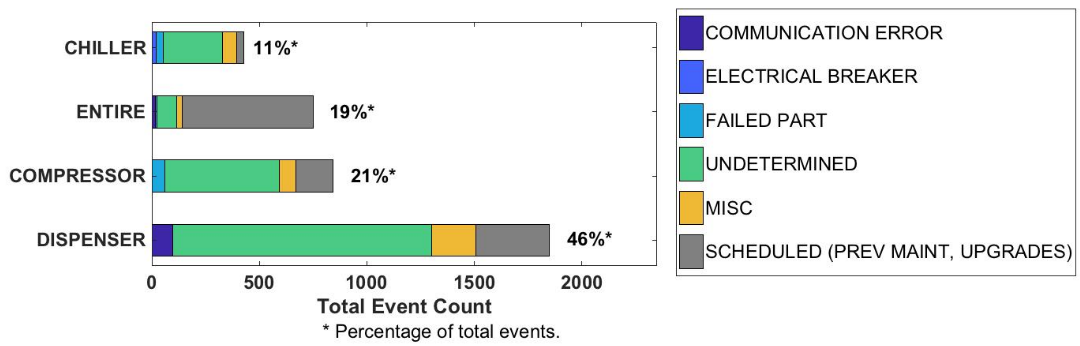

Figure 13. Failure modes for four key maintenance categories, percentage of total events does not sum to 100% because of allocation of events to other (ungraphed) maintenance categories.

As a final means to gain insight into the maintenance of hydrogen stations, we studied correlations among maintenance cause and effects. For this example, we consider the hydrogen dispenser subsystem and dispenser nozzle. For each maintenance event, the station operator, or maintenance technician, completes the data template and the data is categorized, aggregated, and reported through NFCTEC. The NFCTEC researchers interpret the narrative that is input to the database to categorize the types of causes and effects, and to allocate them to components and subsystems. Figure 14, presents the data subset where maintenance was performed on the dispenser subsystem and the failed component is classified as “entire”, which means that either a dispenser component was not identified and entered, or the maintenance events were for the entire dispenser subsystem. As illustrated in Figure 14, the majority of causes were categorized as “undetermined”, and the majority of effects were categorized as either “undetermined”, “hydrogen leaks”, and “alarms”. This example illustrates that when considering maintenance logs for complicated components (such as the entire dispenser subsystem), the probability of having failures for which the root component cause is not known can be high.

In Figure 15, we consider the dispenser nozzle (a subset of the dispenser subsystem) as the subsystem. As illustrated in Figure 15, although undetermined failure effects due to undetermined failure causes was still a large fraction of the maintenance events, this system is small or simple enough that the technician is more easily able to determine and record failure causes and effects. For dispenser nozzles, failures that are root caused by part failures, communication errors, and design flaws are significant sources of unplanned maintenance events.

These examples illustrate that additional data, analysis, and experiments are often needed at subsystem and component level because the undetermined or miscellaneous failure mode is so common when failures are described at system level. In the case when many of the maintenance events are categorized as undetermined, further investigation is needed to evaluate why undetermined was selected. If the cause of failure is unknown and of high priority, root cause analysis should be completed.

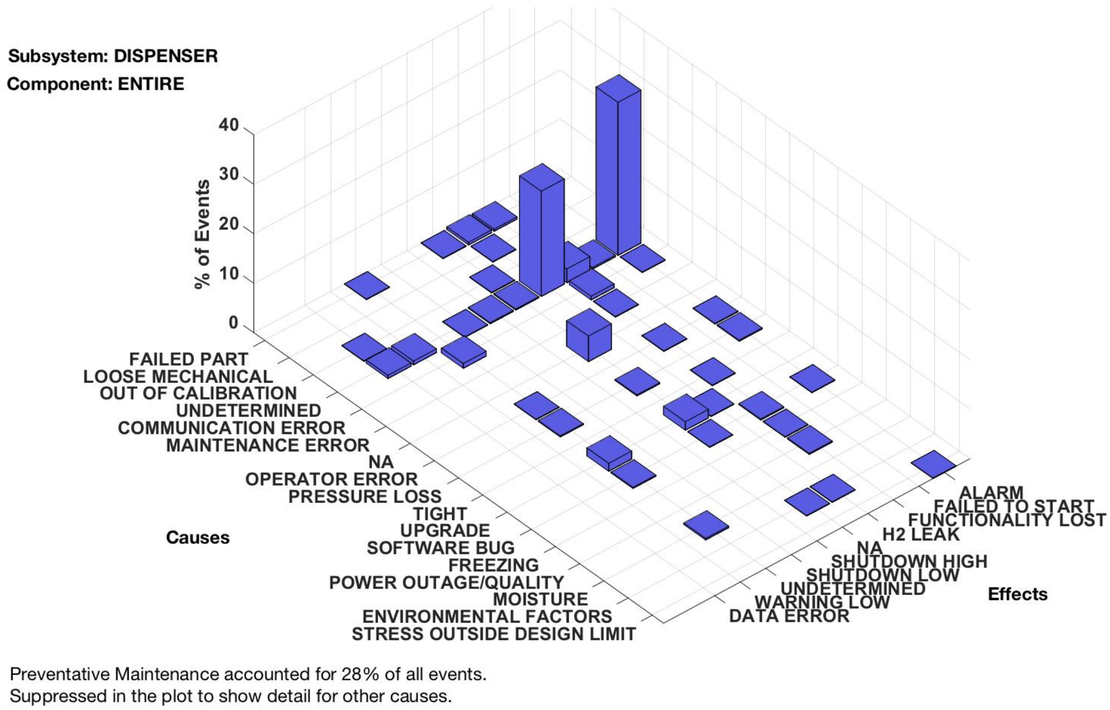

Figure 14. Dispenser maintenance cause and effects—entire

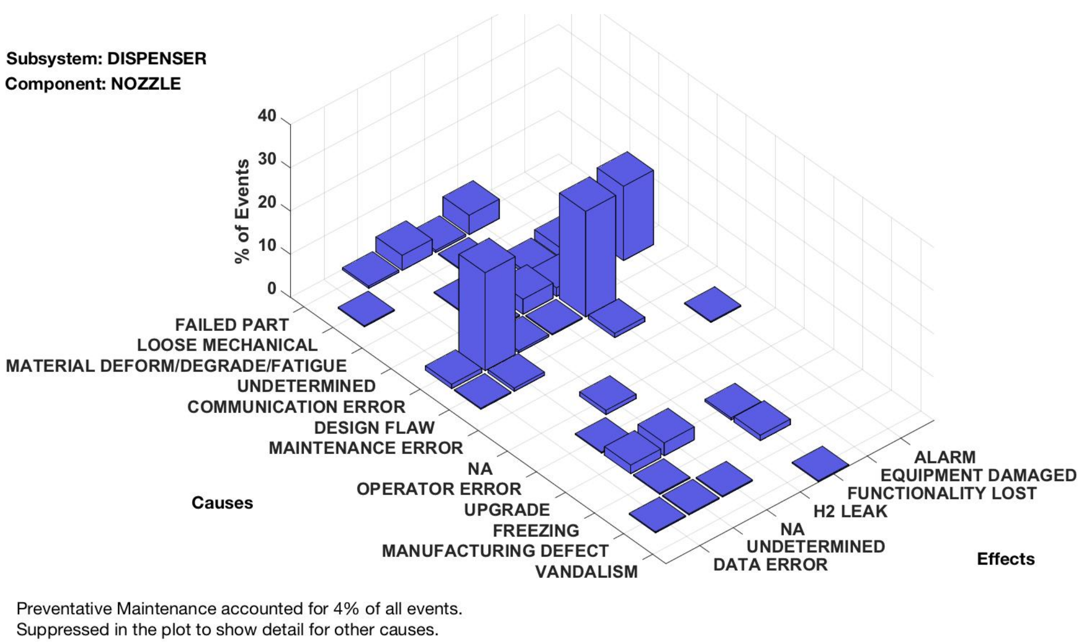

Figure 15. Dispenser maintenance cause and effect—nozzle

4.3.2 Hydrogen Station Reliability

The unscheduled maintenance event data can also be used to quantify station reliability. This section presents the failure rates and reliability growth as a function of the number of fills and by station for 29 stations. For this analysis, the aging variable, *t*, is fill count. Fill count was chosen instead of time (days) or kilograms dispensed (kg) because fill count represents a convenient unit of thermal/pressure cycling, user operation, and control system operation for a hydrogen station. A time-based aging equation may be a more representative station aging variable in a phase of the station lifeycle with higher demand and higher station technology maturity.

Using fill count as the aging parameter for station reliability, the reliability results as a function of fills are presented in Figure 16, which shows the MFBF for the 29 stations by station cumulative fill count. All stations except for one have an MFBF of approximately 500 or less. To provide context with calendar time, the average monthly fill count was just under 600 fills at the end of 2017. Figure 16 also provides insight into the distribution of total fill counts relative to the stations. There are a few high-fill-count stations, but most are grouped on the first half of the x-axis[3]. One failure and unscheduled maintenance visit per month is not adequate to meet retail customers' expectations, as an unscheduled maintenance event may indicate the station is unavailable for fueling. This implies that station reliability is a major problem for current hydrogen stations, yet it does not provide insight into whether failure rates are changing over time.

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[3] Note that the x-axis tick numbers were intentionally left off Figure 16 to obfuscate a secure data set

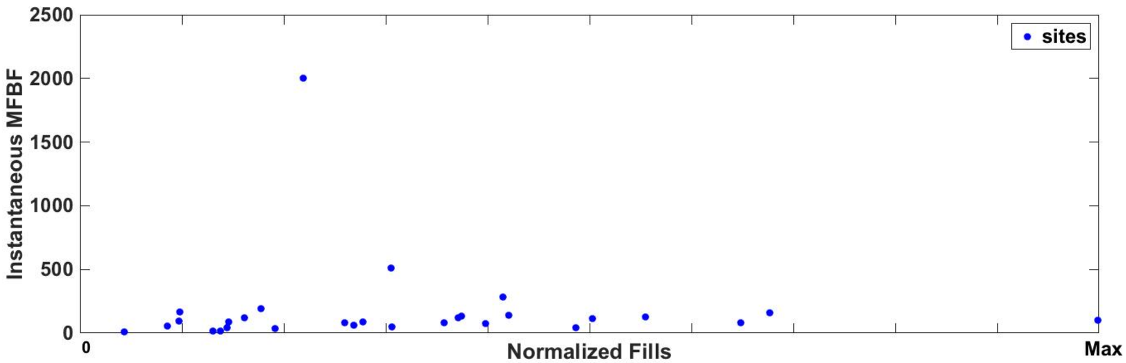

Figure 16. Station MFBF by cumulative fills

Figure 17 illustrates the instantaneous station failure rate at various stages of station life. The station on the far left is the station with the lowest fill count and the station on the far right is the station with the highest fill count. (This sorting may not directly correlate with how long a station has been operational.) Three metrics are shown for each station: the shape parameter for the early failure event history, entire failure event history, and latest 20% of failure events. Shape parameters that are greater than 1 indicate a failure rate that is decreasing as a function of fills. Shape parameters that are less than 1 indicate a failure rate that is increasing as a function of fills. The shape parameter for all failure data and for each station is shown in the blue bar. Out of 29 stations that supplied detailed enough maintenance records, 24 stations have seen a decrease in failure rate, meaning that the number of fills between failures is increasing as the station operates. The early history shape parameter is shown by the red star markers, 15 stations had a shape parameter of greater than 1 meaning that their failure rate was increasing early in their operation lifetime. The early history and last 20% of events (yellow) bar are specified in the figure because reliability growth and the instantaneous failure rate (Equation 3) can vary significantly over the aging parameter. For instance, station #7 has a shape parameter value of approximately half its initial value. The instantaneous failure rate improved for 20 stations in the last 20% of failures per station, while the four stations with the highest total fill count (stations #26–29) saw an increase in failure rate.

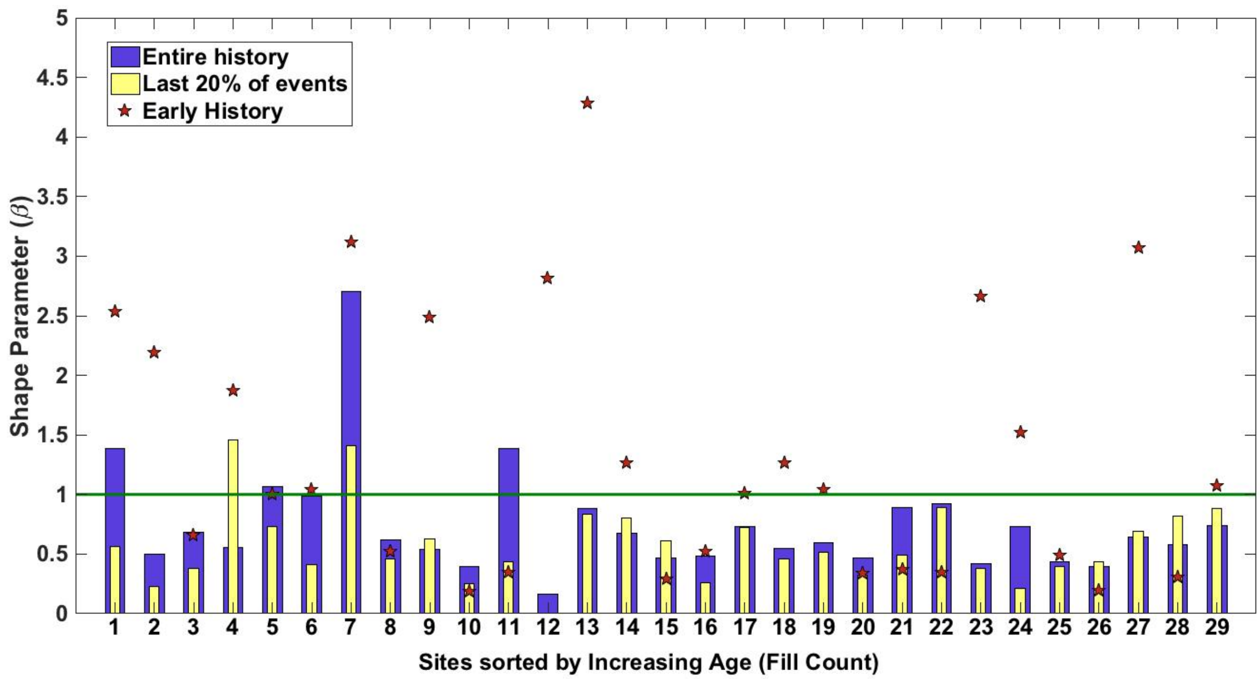

Figure 17. Retail station reliability growth

Comparing station failure rates can be a challenge because the stations are at different operation phases (such as a newly commissioned station), utilization, technology generations, and dispensing capabilities. All station and historical failure rate data were plotted to study how the data fits the trend of a reliability bathtub curve (Figure 18). Individual station operation data like fill count and early (identified by the star) and current failure (identified by the yellow bar) history are shown with various features in Figure 18. Each failure event and accompanying fill count is plotted for all the stations, shown in the blue dot. The x- and y-axes have been limited because only a small percentage of the data exceeds a failure rate of 0.4 and fill count greater than 10. The green line represents a least-squares fit of the scatter data, with a similarity to the left side of the bathtub curve, with the following equation:

$$\rho(t) = 1.3 * 0.62 * Fill^{0.62-1} \tag{6}$$

The heel of the curve is approximately around 1,000 fills, where the MFBF is 17 (the inverse of $\rho(t)$). This is an indication that failures seen today are likely either early or random failures. Fatigue or gaining failures are not in evidence in this dataset yet. One significant caveat is that this is for all stations and all failures, so there is the potential for individual stations to be exhibiting failure behavior that is not captured in this bulk analysis.

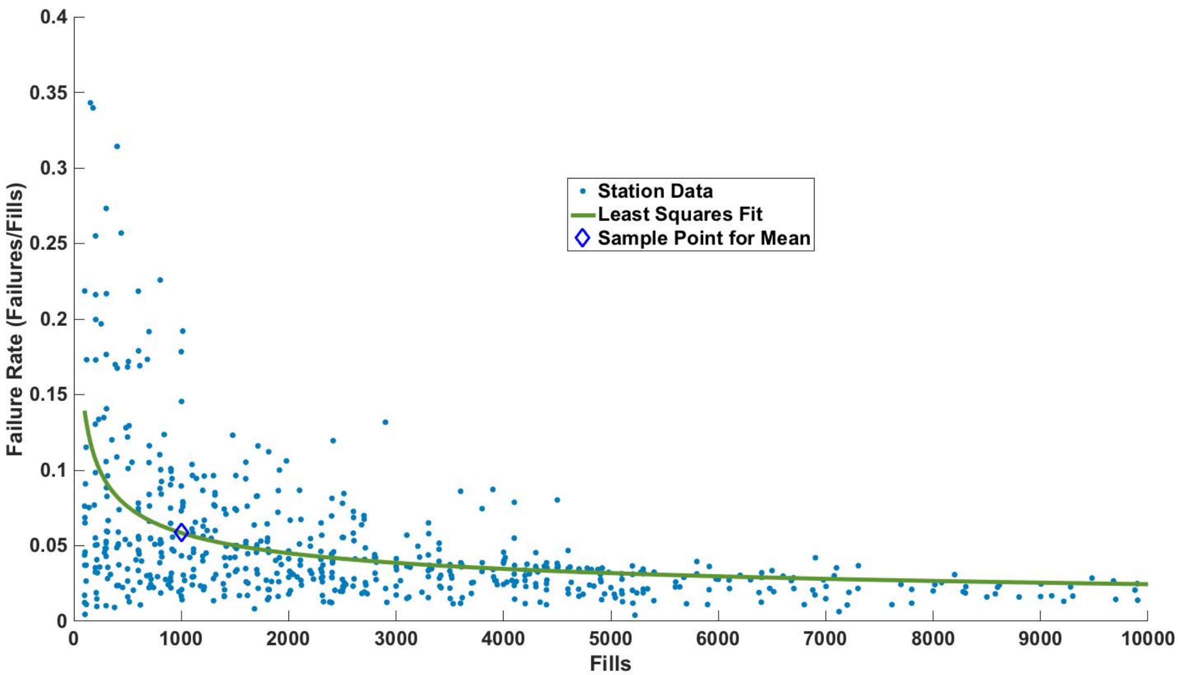

Figure 18. Historical failure rate by fills for retail hydrogen stations

The hydrogen station reliability growth analysis shows that:

- Failure rates are decreasing: most stations have a decreasing rate of failure, which demonstrates positive progress by station operators and equipment suppliers.
- Reliability of most stations has improved compared to their early operation history: about 30% of stations had frequent failures early in the operating period yet approximately 65% of the stations (including all of the stations with an increasing failure rate in the early history) have decreased the rate of failure compared to the early history.

- High fill count may lead to potential failures: the oldest four stations have an increasing failure rate for the last 20% of events, which may indicate failures due to a higher cycle count.
- Failure rates are still too high to achieve mass market acceptance: even with most stations having a decreasing failure rate.

One assumption made in this hydrogen station reliability study is that the reliability has to be as good as a traditional gasoline station. There is limited public information on gasoline station reliability. One study of 41 gas stations and 577 dispensers aimed to decreased frequency of corrective maintenance by optimizing preventative maintenance activities [117]. In this study, three categories were created for high, medium, and low failure stations. The medium failure station category (17 stations and 248 dispensers) had a failure rate of 0.001935 failure/hour/dispenser, which is a mean time between corrective maintenance (MTBCM) activities of 516 hours or 21.5 days. The low failure station category (17 stations and 196 dispensers) had a MTBCM activities of 820 hours or 34 days.

In order to correlate this gasoline MTBCM data with the hydrogen station data, it is necessary to look at the frequency of fills against calendar time. The latest data shows an average of approximately 1,000 fills per month for the studied stations [101]. Station MFBF, shown in Figure 16, shows that the majority of hydrogen stations in this dataset have a MFBF of less than 500, which can be translated to approximately 15 days. This is less than the MTBCM of the medium failure gasoline station category, however this is not to say that this comparison is done with similar data or method so future study could be completed to benchmark hydrogen station reliability against gasoline station or another alternative fueling infrastructure. One additional challenge to meeting the same reliability as a gasoline station is there are significantly fewer hydrogen dispensers than gasoline dispensers. When one hydrogen dispenser is unavailable, it is more likely that there would be a significant impact on the FCEV drivers who may have to drive to another station for hydrogen than for gasoline vehicle drivers. This can be especially problematic as the demand for hydrogen stations increases.

The amount of hydrogen dispensed in 2017 was 4 times what was dispensed in 2016, and at the end of 2017, two stations had a utilization of greater than 80% (based on a daily capacity). These two details indicate that hydrogen demand is changing rapidly, and this has an impact on station maintenance and reliability. For instance, maintenance cost per kilogram is decreasing (Figure 19). This decreasing trend is primarily due to an increase in the amount of hydrogen dispensed. The demand for hydrogen is expected to increase, along with demand for additional hydrogen stations [51]. There are few other inferences from maintenance cost data in that some maintenance is becoming routine and doesn’t require in-depth failure investigation or advanced training. The cost of some replacement parts may also be decreasing with more online stations and bulk purchases [118].

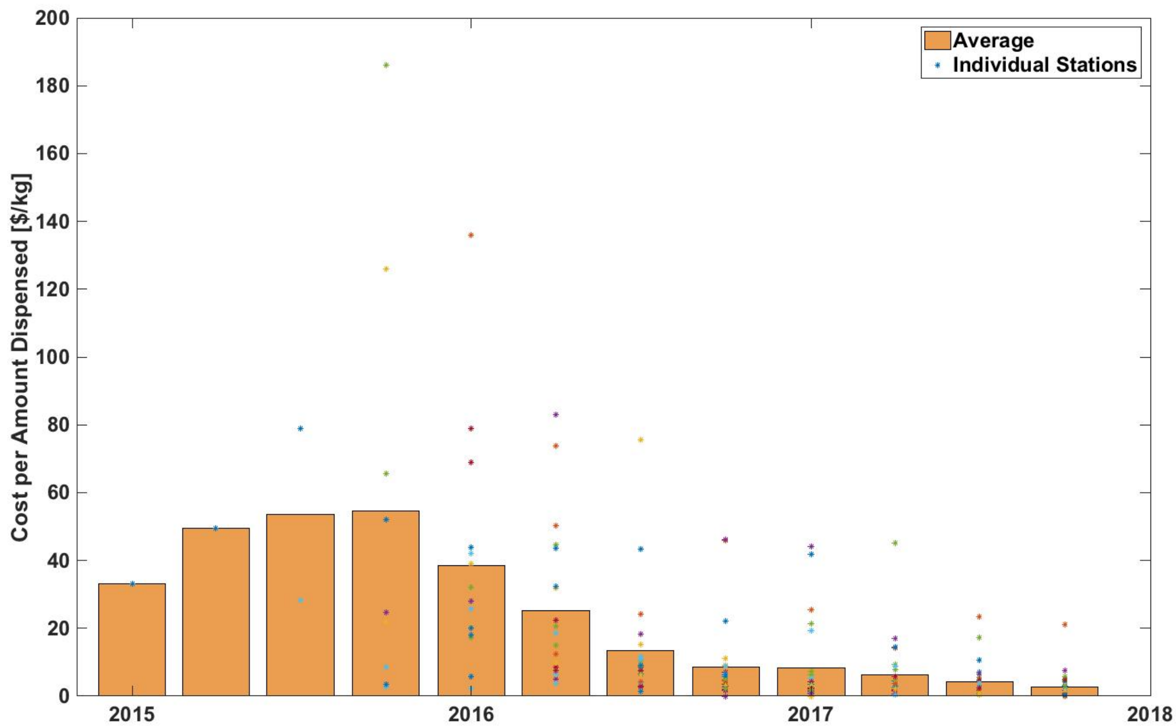

Figure 19. Maintenance cost per kg dispensed over time

4.4. Using Maintenance Data to Improve Hydrogen Station Reliability

Much of the reliability growth analysis presented here has been focused on commonalities and straightforward reviews of station maintenance, which includes both preventative maintenance and unscheduled maintenance due to failures and alarms. One gap in the data for this analysis is that the condition of components at failure is not known, nor is the reason for failure. Condition and cause of failure identification is needed for the development of corrective actions that will improve station reliability. This section covers on-going research for dispensers, a subsystem with the highest count of unscheduled maintenance events (46%) of all stations analyzed.

This in-progress research aims to supply data component condition at failure from laboratory-controlled experiments. Controlled failure condition data like this will help researchers and operators answer questions about how differently a component fails based on the field operating conditions. These additional scientific findings combined with the maintenance and reliability benchmarking completed so far provide researchers and operators valuable information about early failures that are due to new stations coming on line, how experience gathered during station O&M can improve reliability, and how station failures change as a station ages in both cumulative fill counts and time.

4.4.1 Failure Condition Data Experiments

Recurring failures, especially those which are experienced at high utilization, are ideal failures to focus on for additional research. In the past, the compressor system was the leading maintenance category, but compressor research and development has contributed to an improved compressor system MFBF. For example, NREL researchers studied compressor reliability and provided data on physics of failure of compressor seals. This research identified metal fragments as a major contributor to seal failure. Also, lubricants used on elastomer seals were found downstream of compressor systems, which identified a need to use hydrogen-compatible lubricants [119]. In addition, the project showed that seal failures are the main driver for compressor downtime, that typical failures take more than 2 hours to repair with multiple people, and that downtime can be avoided with real-time monitoring of the compressor leak detection circuit [120].

The results of this research show that dispensers are a leading category for unscheduled maintenance. In response, NREL has developed a set of active controlled experiments on dispenser subsystem reliability. During a fill, the dispenser system components experience a rapid change in both pressure (ambient to 70 MPa) and temperature (ambient to -40°C). These rapid pressure and temperature changes are thought to be a primary contributor to dispenser component failures. Benchmark data along with hardware experiments to improve dispenser reliability provide performance data back to manufacturers on how their components perform under controlled, retail-like conditions, with particular attention given to operating conditions that should generate valuable failure data. Extreme operating conditions and the external interfaces, which include both the driver and the vehicle, make for an interesting and challenging dispenser system and a top priority for reliable and safe operation.

Therefore, NREL's hydrogen dispenser reliability research is focused on critical dispenser components. The hose reliability project is an ongoing effort at NREL's Hydrogen Infrastructure Testing and Research Facility (HITRF). The project utilizes a six-axis robot to mimic the mechanical bending and twisting of a person fueling their vehicle. The system performs a fill like what would be experienced in the field. Current results, from over 5,000 fill cycles, show that leaks tend to happen at the metal crimp-to-hose connection [121]. This project was initiated during a period of low station utilization and was first focused on completing a high fill count. With this data as a baseline for accelerated hose reliability, additional features are planned that include additional hose stresses such as varying interface angles and other thermal and mechanical conditions.

Benchmark data from the field lacks the design of experiments that are best able to identify failure conditions and causes. Another active NREL research project is the dispenser reliability project [122], which measures the mean fills and kilograms dispensed between failures of hydrogen components subjected to pressures, ramp rates, and flow rates similar to light-duty FCEV fueling. The project is exploring three different required cooling levels, at -40°C, -20°C, and 0°C, with -40°C being the current standard for light-duty vehicle fueling. The experiment (Figure 20) consists of flowing hydrogen through eight "dispenser like" systems simultaneously. The flow rates and ramp rates are in the range of a typical SAE J2601 fill. The components are ramped at ~17.5 MPa/min at a flow rate of ~0.5 kg/min through each component. The systems are packaged with two dispenser sets in series and four sets in parallel to complete the full system. The flow rate, ramp rate, and gas temperature are controlled on the front end with a research dispenser. The back end has a flow controller as well as a recycle loop to accelerate system recovery time at NREL's HITRF.

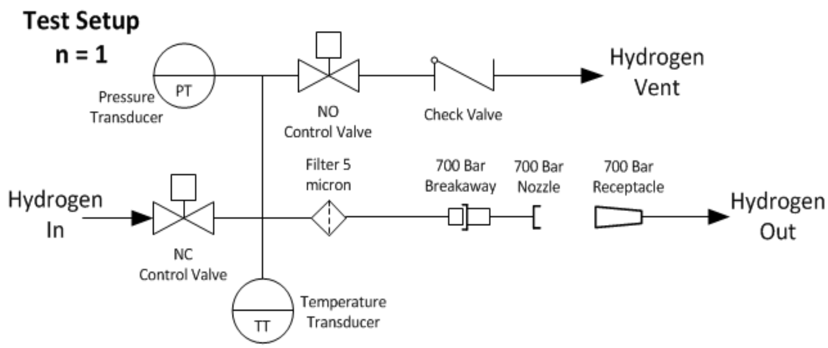

Figure 20. Dispenser reliability test setup

4.4.2 Data to Drive Failure Investigation and Reliability Improvement Efforts

Reliability improvement efforts are most effective when the improvements are informed by data, both from real-world operation and controlled reliability experiments. The retail hydrogen station maintenance data studied to date has many instances of undetermined failure modes. The combination of a lack of failure condition data with the maintenance benchmarking is guiding NREL's hardware research. More specifically, it is guiding what systems and operating conditions are studied. A basic objective of this research is to provide controlled data that can accurately and consistently identify failure conditions. Data from these experiments is expected to guide failure analysis only on the highest-priority components, which should generate meaningful feedback to equipment manufacturers for product improvements. This is a methodical process, driven by both field and lab data, to identify failures and improvements with more complicated and expensive diagnostic studies and instrumentation. For example, results from the dispenser reliability project will inform experimental setup and test plans based on the highest-frequency component failures and the accompanying conditions that generated failures. The future experiments will dissect the components to identify failure root cause with various mechanical, thermal, and humidity stresses and material investigations.

4.5. Conclusions

Hydrogen stations play a critical role in the supply of hydrogen to fuel cell technologies like cars, trucks, and buses. An exponential increase in hydrogen demand in California has pushed stations to be able to reliably dispense hydrogen whenever the FCEV driver pulls up to the station. Yet the station reliability is lower than what the customers expect, as identified by the results presented here, and when compared with traditional gasoline station reliability. There are some concessions that can be made in this comparison because gasoline and hydrogen stations are at different commercialization phases and data processing may not have been similar between the gasoline and hydrogen station analyses. The maintenance benchmarking results presented here by category, frequency, labor time, and failure cause/effect create a trackable status of station maintenance and reliability. The reliability analysis has identified the two leading maintenance categories as dispensers and compressors, which represent 67% of the retail station maintenance events. Crow-AMSAA was the analysis method of maintenance data from hydrogen stations, where the majority of hydrogen stations have a MFBF of less than 500 fills, which can roughly translate to every 15 days. This is lower than the MTBCM of 21.5 days for the medium failure gasoline station group.

Results to date show improvements in MFBF and changes in the leading maintenance category as a function of time. There have been target component reliability improvements, for example with compressors, and lessons learned from the initial station deployments that make some failures only a one-time event. A couple of years ago, compressors were the leading maintenance category, but compressors have improved with updated technologies, preventative maintenance strategies, control strategies, new designs, and increased station utilization. A reliability improvement program is expected to also include changes in components and operation that is informed from laboratory findings to reduce failures.

There remains a gap in the understanding of leading causes for failures in the hydrogen station highlighting the need for systematic experiments investigating root causes of failures, especially for high priority subsystems like dispenser. The dispenser system reliability experiments, currently in progress, are expected to support root cause failure investigation. The controlled operating conditions of these accelerated reliability experiments will be the basis for future experiments to quickly replicate failures that can be deconstructed to identify the failure cause and lead to potential improvements for equipment manufacturers. This should present options to improve hydrogen stations, which in turn supports a critical pathway of H2@Scale, enabling hydrogen mobility solutions. The next chapter continues the research through a study on the FCEV demand and how predictive future demand supports station O&M strategies.

CHAPTER 5 – PREDICTING DEMAND FOR HYDROGEN STATION FUELING

5. Introduction to Hydrogen Demand

A hydrogen station serves the purpose of fueling a FCEV and the station controls provide the basic function of safely dispensing hydrogen from the station to the vehicle. These same controls also have the potential to improve the effectiveness of hydrogen station O&M. It is expected that a station control strategy that integrates a prediction of future fueling demand can identify ideal times for maintenance and provide data to inform decisions driven by economic trade-offs. This study describes the development and value of a model that simulates stochastic future demand at a hydrogen filling station. The predictive hydrogen demand model described in this chapter is trained from mathematical models constructed from actual hydrogen fill count, amount, and frequency data. This is a first-of-its kind, study on predicting future hydrogen demand by the time of day (e.g., hour-by-hour intervals) and day of week. This study can be used for developing hydrogen station requirements and O&M strategies and to assess the impact of demand variations and scenarios.

This chapter presents the current status of hydrogen demand and hydrogen station utilization based on real-world station operation data, as well as the model development methods and a set of sample results. Discussion and conclusions concentrate on the value and use of the proposed model for improved station economics and effectiveness.

5.1. Hydrogen Station Utilization

Between 2017-2018, the customer demand for hydrogen for fuel cell electric vehicles (FCEVs) increased more than 2 times, to more than 913,000 kilograms[4]. The FCEV market is driving this growth in the United States, with an estimated 6,000 FCEVs on the road and a network of 39 operational, retail hydrogen stations (24 more planned stations) supporting these vehicles [22], [47]. This hydrogen infrastructure serves public and private fleets of light-duty passenger cars, trucks, buses, forklifts, and ground-support equipment. These mobility-focused FCEV applications have demonstrated benefits in terms of vehicle performance (e.g., fueling time, range) and economics (e.g., total cost of ownership) [123], but the long-term success of the hydrogen vehicles and infrastructure is far from assured. This emerging market is eager for more stations, at a higher throughput and an economically viable price point. The development cycle for new hydrogen stations is being compressed to meet the requirements of a growing market. This compressed development cycle supports acceleration of new vehicles entering the marketplace but may also increase the risk of stranded infrastructure, where even modern hydrogen stations may be too costly, too slow, and not flexible enough to meet future needs. One way to manage some of this risk is through an understanding of how the hydrogen demand, or fill profile, will change over the operational life of the station.

Even considering its recent growth, demand for hydrogen for vehicles is still low compared to demand for gasoline for vehicles. For example, there are approximately 60 operational and planned hydrogen stations (concentrated in California, United States). In

[4] a kilogram of hydrogen has approximately the same energy content as a gallon of gasoline

comparison, there are more than 8,000 gasoline stations in California, and more than 120,000 convenience stores selling gasoline in the United States, with 765,000 dispensers and approximately 1.4 million fueling nozzles [124]. Approximately 39 million gasoline fills take place in the United States every day, corresponding to 26 cars per fueling nozzle per day or 325 gas-powered vehicles per day for a station with 12 gasoline fueling nozzles. Hydrogen-fueled FCEVs and their infrastructure must grow in function and scale to rival gasoline vehicles and infrastructure if they are to become a mass-market transportation solution that can realize economic, sustainability, and consumer preference benefits [125].

Many factors influence and determine the success of hydrogen infrastructure, and this infrastructure is a prerequisite to marketing and acceptance of FCEV technologies. The deployment of hydrogen stations has increased (primarily in California in the US) [33] and more fuel cell technologies are also commercially available (e.g., forklifts and buses), or have been developed/introduced to the market (e.g., trucks and ground-support equipment). One important influencing factor is the ease of use, accessibility and availability of hydrogen stations. A hydrogen station has many of the external features of a gasoline station, such as a dispenser and a user interface for the transaction details and payment. It also has storage and the needed equipment, controls, and safety to supply the hydrogen quickly. Analysis of real-world use for fuel cell light-duty vehicles and hydrogen stations has shown behavioral trends similar to gasoline fills and driving, including time of trips, time of fills, range, and fill time [33], [8], [126]. Finally, and perhaps most importantly, cost of hydrogen is an important factor for hydrogen station market success.

Consider that a basic objective of a hydrogen or gasoline station is to safely and economically provide a fuel to the consumer. An understanding of consumer demand is then necessary to support the development, deployment, and operation of the hydrogen station. Yet, there is little research in the scientific literature regarding modeling or measuring hydrogen station demand or utilization. Demand uncertainty is shown to result in uncertainty in deployment and supply analyses [127]. Our literature search (completed in March 2019) for journal articles with keywords “hydrogen station demand or utilization” resulted in only three results [128], [129], [130]. These studies view hydrogen demand from a regional perspective to understand implications on locations and cost, but these studies do not have information or models of the day-by-day or hour-by-hour changes in demand. Much of the scientific literature regarding hydrogen infrastructure and stations deals with deployment topics, seeking to optimize region, location, and size [96], [48], [102], [68], [103]. These analyses make general assumptions about the number of on-road light-duty fuel cell vehicles, which create bulk hydrogen demand scenarios. Bulk demand scenarios generally are based on region and total fleet size. They don’t include change in demand over time, either hour-to-hour or day-to-day [131], [132]. Expanding the search of scientific literature to include terms such as “operation” (18 results), the literature focuses on strategies for existing, small-scale stations or bespoke future options. The results of this literature review show that there is a significant gap in the literature published to date on predicting the hourly demand for hydrogen fueling for vehicles. This gap is primarily due to the fact that operations data is limited and not easily attained, especially for datasets that can be extended across multiple hydrogen stations and operators. In addition, hydrogen demand is constantly changing as the technologies and markets change. For example, fast fill technologies, renewables-integrated electrolyzer-based stations, and long-haul fuel cell trucks have all changed the dynamics of hydrogen station operation and hydrogen demand.

The authors are in a unique position to develop a predictive hydrogen demand model having gathered proprietary hydrogen station operation data with collaborative research partnerships, the design, development, operation, and the maintenance of a hydrogen infrastructure research facility. The hypothesis is that existing data from hydrogen and gasoline fills can be used to build a predictive demand model that will improve hydrogen station O&M by factoring in future fills with a current understanding of the station state. Neither the current hydrogen or limited gasoline fill data are sufficient for predicting future demand because the number of vehicles, number of stations, and station availability change frequently. Future demand has the potential to be many orders of magnitude higher than what is seen currently at hydrogen stations. These two gaps create a need for a model that can connect a path between current and future hydrogen demand conditions, with the ability to correct and change along the way.

By predicting demand—that is, when and how much hydrogen is needed for a fill and at what frequency—this study seeks to mitigate the risk of investing and operating to build a lasting business case for hydrogen stations. Funding, designing, and building a station when the market for hydrogen is changing rapidly is a challenge, and station operators must identify ways to rapidly be economically stable while handling a demand that is expected to increase steadily. The demand model has the potential to be a tool used by station developers and operators to make informed decisions on equipment specifications and size, and O&M strategies. Many station operators and policy makers are rightly focused on the near-term challenges of enabling and growing a market. Fine-tuning stations based on a predictive demand model does not likely make sense at this stage. Yet, in the past few years the hydrogen station market has moved from a precommercial phase to an emerging-market phase. This new market phase requires higher reliability, improved customer service, and a more refined approach to understanding and managing hourly, daily, and weekly consumer demand. Therefore, the creation of a predictive demand model capable of adapting to demand changes will support hydrogen station operation in the near-future, working in parallel with technological and operation advancements to support a successful hydrogen fueling market.

This article is organized as follows. Section 5.2 describes the methods to estimate the station types, fill frequency, fill amount, fill rate, time between fills, and the station state (i.e., filling, in standby ready to fill). With multiple types expected for future hydrogen stations, we present the predictive demand model results for an Urban Medium station type (5,000 kg/week) in Section 5.3. Predicting demand can be implemented for various sizing, operation, and maintenance strategies as discussed in Section 5.4. Lastly, Section 5.5 presents the conclusions.

5.2. Demand Analysis Methods

The model is built on a framework that can project future fueling conditions, but can adapt based on available, real-world data. Previous hydrogen demand models assume constant demand as a function of yearly or daily time scales [133], [38], [96], [134], [103], [135]. This assumption of constant demand can be justified early in the commercialization phase of the stations when demand is low, and the station may be underutilized, or for analyses studying a wide region and/or time period. Alternatively, a purely data-driven approach, where time histories of fills can be replayed to populate demand profiles could be effective, but these methods can be stymied by the low data availability for hydrogen stations, and the need for broad extrapolations to model hydrogen station utilization as demand changes in the future.

This study seeks to construct a modeling framework that is based on fitting distributions to broad operational datasets. These distributions are then sampled to construct synthetic operational data specific to a particular station type, bulk hydrogen demand, week day, and time of day. The proposed analysis utilizes real-world fill data for training and validation. The real-world data are from the NFCTEC which includes data from more than 465,000 fills from 30 hydrogen stations. The analysis will be able to adapt to future changes in vehicle deployment and station use as more real-world data becomes available. Uncertainty is inherently included in this probabilistic model, enabling stochastic future demand predictions.

The model is composed of four building blocks, as illustrated in Figure 21. The input block (Step 1) interfaces with the user and accepts the following parameters: time period, time interval, weekly demand target, probability limit (used for prediction), fill type (e.g., light-duty or heavy-duty), and max fill amount (used for data processing). The data generation block uses the variables defined in Step 1 to determine which measured datasets can be used for training (e.g., NFCTEC aggregated fill data). Step 2 creates a representative fill data set for the training step, Step 3. The training block fits filling distributions (frequency, rate, amount, and time) used for the prediction step, Step 4. The prediction block evaluates the probability that a station is in either a fill state or a standby state, based on probability interpretation and fill sequencing for each time interval. The prediction output translates the station state into a time history of station fill frequency and quantity as a function of time.

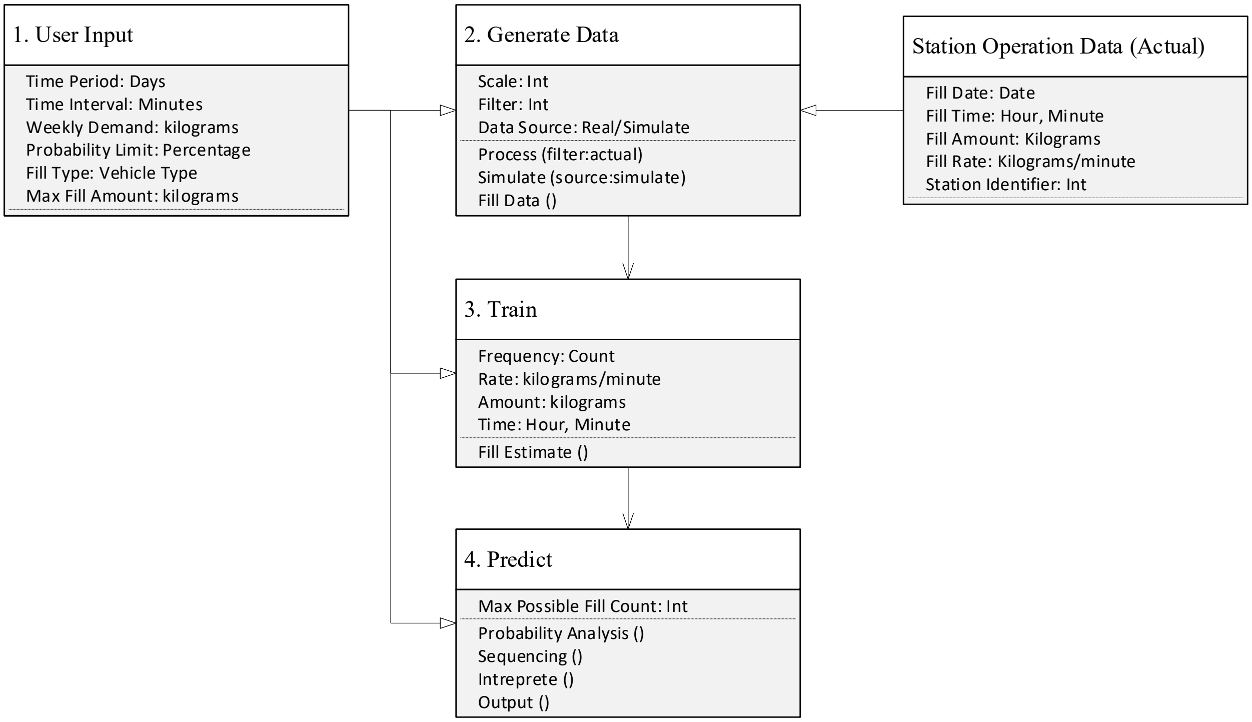

Figure 21. Predictive demand model development and validation flow diagram

5.2.1 Step 1: User Input

The user inputs determine the conditions under which the hydrogen demand will be simulated. The user inputs the relevant simulation time span, and the type of hydrogen station that will be simulated.

Hydrogen demand is not the same for all station types or locations, so the model must distinguish between station type and location to provide useful data for making informed design- and operation-related decisions. This study begins by classifying hydrogen stations according to their location and usage characteristics. These classifications are based on analogous classifications of gasoline stations, as presented in Table 6. The location of the station is classified as either an urban station, or a community/rural/connector station under the assertion that these locations have different usage characteristics. An urban station may be a street corner station, at a major intersection, or collocated with a "big box" store. A connector station is a rural/suburban station with on-off access to major highways but may not be close to large population areas. The scale of the station is classified by its weekly fill amount. Current hydrogen stations are classified as either small or large (indicating the highest used hydrogen stations deployed to date). In the future, the scale of hydrogen stations is expected to converge to the scale of current gasoline stations. We classify future hydrogen stations as small, medium and large scale, by analogy to current currently deployed gasoline fueling stations, yet the future large hydrogen station is still small compared with modern high-use gasoline stations.

Table 6. Hydrogen Station Classification Scheme

Type	Weekly Fill Amount	Weekly Fill Count
Current—Small[1]	250 kg/week	187 fills/week
Current—Large[1]	750 kg/week	337 fills/week
Urban—Small[2]	2,000 kg/week	645 fills/week
Urban—Medium[2]	5,000 kg/week	1,612 fills/week
Urban—Large[2]	10,000 kg/week	3,387 fills/week
Community/Rural/Connector—Average Medium[2]	1,000 kg/week	322 fills/week

1. Based on current hydrogen station demand NFCTEC data.
2. Based on future estimates for hydrogen station demand from the gasoline fueling trend, using a consistent fill amount (3.1 kg/fill) to provide a general sense on the number of fills and amounts per day.

5.2.2 Step 2: Data Generation

We have utilized two primary data sets for training the predictive demand model. One source is the hydrogen station fueling data analyzed through the NFCTEC. The data used for the NFCTEC analysis is supplied to NFCTEC every 1 to 3 months by station operators. The data is processed, analyzed, aggregated, and published typically every 6 months. The published results are assembled in a manner that does not reveal individual proprietary information while providing data on technical capabilities, safety, cost, and trends. The NFCTEC collects, analyzes, and reports on hydrogen infrastructure operation, maintenance, and safety data for fuel cell systems and infrastructure from more than 10 project partners [72].

The other data source is a study of hydrogen delivery options [135] which includes data on gasoline fueling data trends provided by Chevron. These data were used to determine an hourly fuel-demand profile grouped by day of the week and are based on an average Chevron station daily dispensing amount of 4,400 gallons. The profile was published with a percentage of the daily transactions, so it can scale with different station capabilities and weekly dispensing amounts. A challenge in using this gasoline data is that it represents the demand for fuel in a fully-realized gasoline market. It may or may not represent fueling trends for hydrogen FCEVs, in either the near or far term. Figure 22 shows aggregated data from all NFCTEC hydrogen fills, presented as a function of the time of day. The maximum that a station is dispensing is approximately 750 kg/week (> 90 kg/day Monday through Friday) and the average of all stations dispensing is approximately 250 kg/week (~30 kg/day Monday through Friday). A statistical comparison of the hydrogen and gasoline distributions (two-sample Kolmogorov-Smirnov test, p=0.8), indicate that the distributions are similar. Therefore, this study uses both the hydrogen and gasoline hourly distributions of fueling events to represent current and future fueling trends.

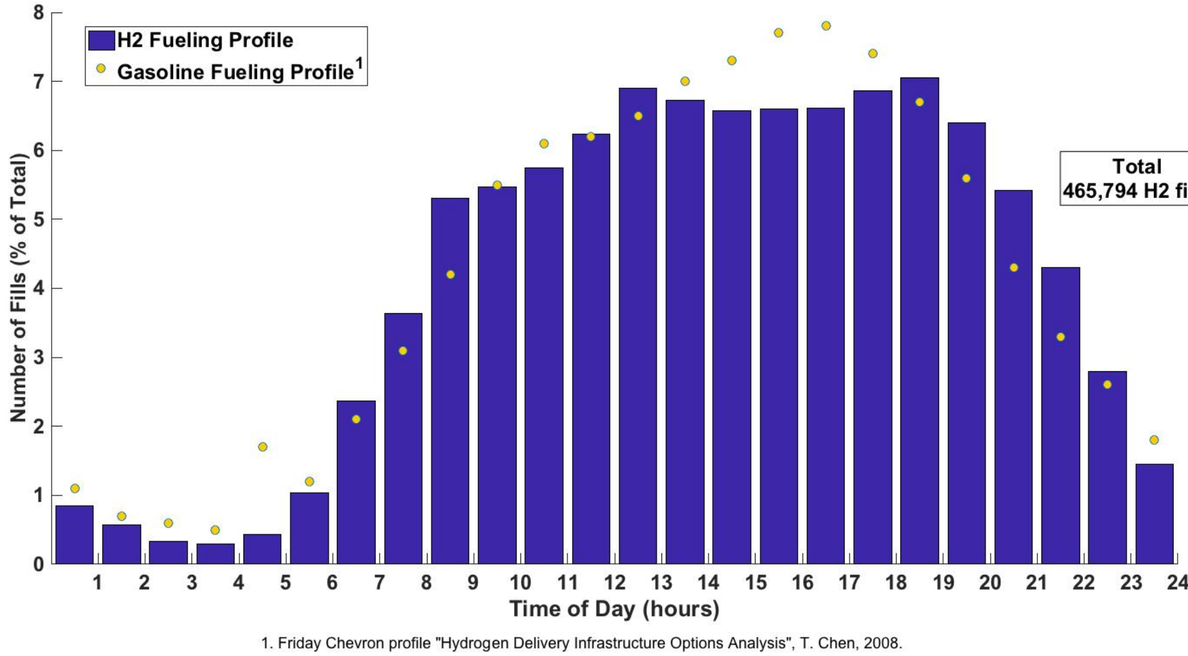

Figure 22. Fill time of day based on retail station data

5.2.3 Step 3: Training

The objective of this study is to predict the rate at which hydrogen will be demanded from present and future hydrogen stations. This work uses a probability model to predict the rate of arrival of vehicles at the hydrogen station, and another probability model to predict the fill quantity for each vehicle.

To determine the fill probability, a fill is considered a discrete event in this analysis and a mean event rate is determined for each time interval over each time period of interest based on a Poisson process. The Poisson process, a common counting process, is used in this analysis because the time at which each hydrogen fill is demanded is assumed random and independent of the timing of the previous fill. The number and time of fills is not constant throughout the day (e.g., there are typically more fills in the afternoon than in the morning), so the arrival of vehicles to a station is modeled as a nonhomogeneous Poisson process, thus we use the Poisson distribution to estimate the mean rate of arrivals per a discrete time interval.

The probability of a certain fill count within a given time interval is defined by the probability density function (Equation 7). Let Y represent the number of events (i.e., fills) in a given period, and let λ be the mean rate of arrivals, then for some y we have,

$$\mathrm{P(Y = y)} = \mathrm{p}(y;\lambda) = \begin{cases} e^{-\lambda}\frac{\lambda^{y}}{y!} & for\ y \in \{0,1,2,\ldots\} \\ 0 & otherwise \end{cases} \tag{7}$$

and,

$$P(Y \le y) = F(y;\lambda) = \sum_{i=0}^{y} \frac{e^{-\lambda}\lambda^{i}}{i!} \tag{8}$$

The probability of the number of events in the time interval is repeated for the total number of time intervals of interest (e.g., 15-minutes intervals for a 1-week time period). The maximum likelihood estimator is used for the Poisson distribution, $\hat{\lambda}$, for each time interval based on the user input. The fill probability is used in the predictive model to determine the fill count for each time interval within the period specified.

To estimate the fill amount and rate, the model must be able to estimate the amount and dispensing rate (kilograms/minute) based on statistics of past fills. Amount of hydrogen and rate per fill depend on the vehicle's on-board storage volume, its state of charge, and the station's ability to complete a full fill. Therefore, both dispensing rates and amounts are random variables and thus can be modeled by fitted distributions.

The fill amount and dispensing rate distributions are fit using current hydrogen station data. The current distribution of fill amount for NFCTEC stations is shown in Figure 23, showing that the average is 3.1 kg per fill. Because of the heavy negative skew and large kurtosis, a transformation to make the fill amounts normal was not viable, so a kernel density estimation for the probability distribution function (Equation 9) of amount of fuel per fill was used. The kernel density estimation was generated for the training data, where X is a random variable representing the fill amount (in kg),

$$\widehat{p_n}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right) \tag{9}$$

where $K(\cdot)$ is the normal kernel (Equation 10),

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}} \tag{10}$$

and where $h > 0$ is the bandwidth (i.e., smoothing parameter) for sample amount values X_i. Here, h is fit based on the training data to ensure that neither over-smoothing or under-smoothing occurs. Equations 9 and 10 define the fitted distribution of hydrogen fill amount for present and future stations, enabled us to generate a random sample of simulated fill amounts by the inverse transform sampling method. A statistical comparison of the amounts and distribution fit (two-sample Kolmogorov-Smirnov test, p=0.6), indicate that the distributions are similar.

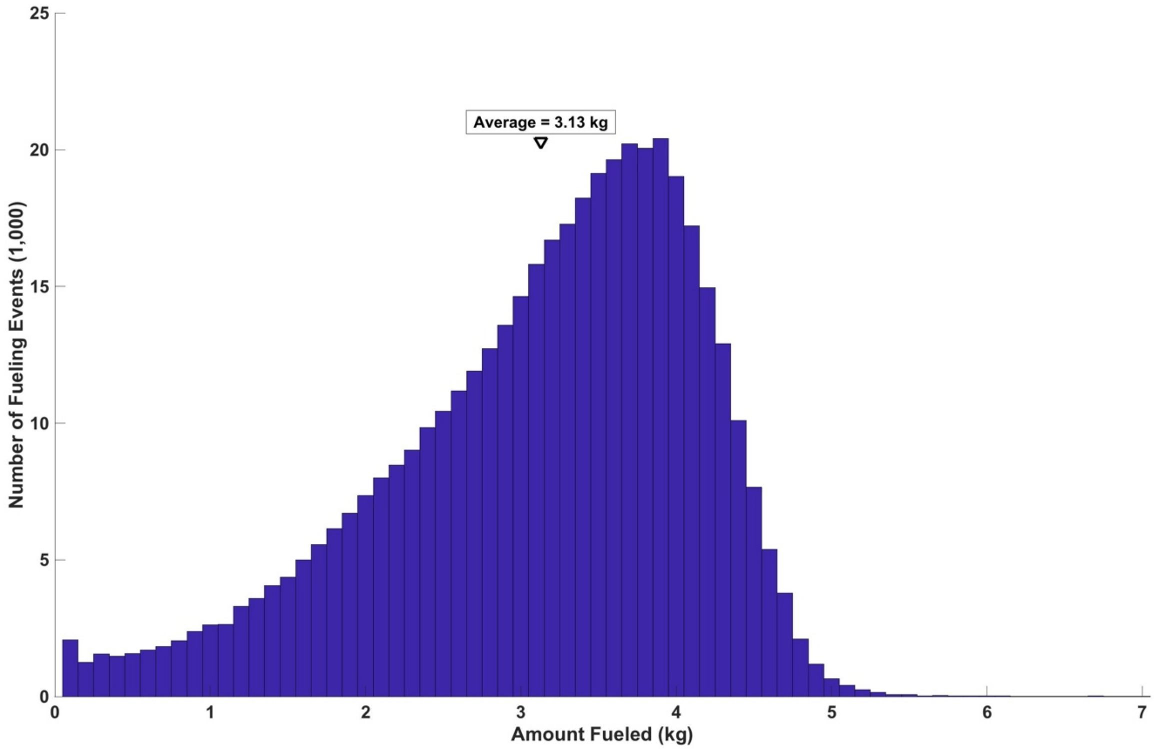

Figure 23. Hydrogen station fueling amounts per NFCTEC data

Hydrogen fill rates are defined by the protocol for light-duty vehicle fueling [72], with minor variations possible due to the station capabilities. The distribution of fill rate (averaged over each fueling event) for all NFCTEC data is shown in Figure 24, with an event-averaged rate of 0.9 kg/min. The normal distribution is used to model the fill rates and to create estimates of fill rates per specific time intervals needed for the predictive demand model. A statistical comparison of the rates and distribution fit (two-sample Kolmogorov-Smirnov test, p=0.8), indicate that the distributions are similar.

Let Z be a normally distributed random variable (Equation 11) representing fill rate. Then for mean μ and variance σ,

$$P(z|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \quad (11)$$

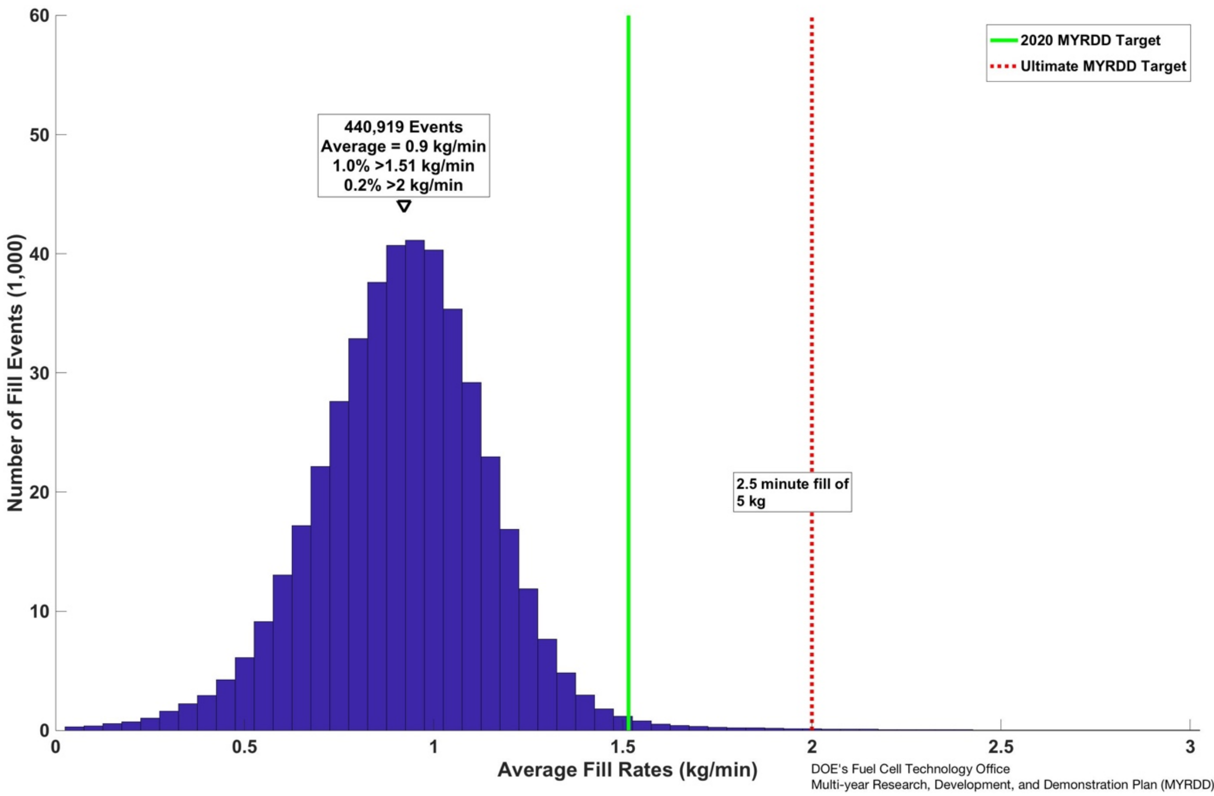

Figure 24. Hydrogen station fueling rates within the NFCTEC dataset, with comparisons to the Department of Energy Fuel Cell Technology Office targets

The estimate for the arrival time (within time interval i) of a fill event, T_i, is based on the waiting time between arrivals, W_i. Waiting times are randomly generated according to an exponential distribution with mean fill event rate λ_i. Therefore, the probability that the waiting time W is less than or equal to a specified wait time (w) is shown in Equation 12.

$$P(W \leq w) = \lambda e^{-\lambda w} \tag{12}$$

Arrivals to the station occur according to a Poisson distribution (Equation 7). Each vehicle's fueling time is calculated as its random fueling amount (x) divided by its associated random filling rate (z). Therefore, arrivals occur according to a Poisson process where the wait time between arrivals is exponential, arrivals occur at the end of a waiting time, and the amount of time a vehicle remains at the station is subject to fueling amount and filling rate. The estimated wait time W is used to determine time dependent predictions like the fill start time within a time interval—which occurs at the end of a waiting time.

5.2.4 Step 4: Prediction

In Step 4, the model integrates the various data estimated from Step 3 to generate a cohesive prediction of the time history of fill count, fill amount, and fill rate. The prediction model utilizes the fill statistics from Step 3 and estimates future station fill states based on fill probabilities for each time interval.

From the perspective of the hydrogen station, each vehicle fill is modeled as a random independent, event, where each vehicle's fueling characteristics (e.g., arrival time, fill rate, fuel mass) are uncorrelated to the characteristics of the previous vehicle. A continuous-time Markov process was selected to model the probability of each state per time interval, due to its stochastic nature where the events are independent. A hydrogen station Markov system (Figure 25) is defined with three states: state A is available but not fueling, state B is available and fueling, and state C is unavailable due to maintenance. Fill times are dependent on fill amount (kg) and rate (kg/min). Fill times corresponds to the length of time the station is in state B and waiting times corresponds to the length of time the station is in state A. The current model, as described in the remainder of this article, focuses on states A and B. The inclusion of a probability estimates for station unavailability is suggested for future work.

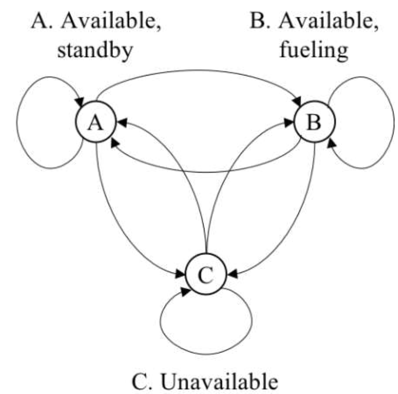

Figure 25. State transition diagram for states A, B, and C

Let $N(t)$ be a stochastic process where t is time (Equation 13). Then, $N(t)$ is a Markov process for every n and $t_1 < t_2 \ldots < t_n$

$$P(N(t_n) \leq N_n \mid N\big(t_{n-1}, \ldots, N(t_1)\big) = P(N(t_n) \ \leq N_n \mid N(t_{n-1})) \quad (13)$$

Each iteration, n, has an associated state vector for the probability of transitioning from each state, which is based only on transitioning from the previous state to a future state. That is, the probability of the station transitioning into a future state depends only on the current state of the station (Markov property, Equation 13). All states are recurrent, as the station can return to the same state as the previous state (e.g., a back-to-back fill which has a wait time of 0 minutes). Ques are not considered and could be included in a future iteration. The transition matrix, ***P***, chain (Equation 14) is also aperiodic and irreducible. The matrix is of the following form where for all $m \ \in [0, \infty)$ and for all states $i, j \ \in S$ for the state space $S = \{State\ A, State\ B\}$,

$$\mathrm{P_{ij}} = P(X_{m+1} = j \mid X_m = i) \quad (14)$$

The model predicts the probability of the state the station state based on the distribution for arrivals and time intervals and time in the state, which is independent of the station's most previous state. To look at long-term system behavior, the limiting distribution was computed for each transition matrix. The limiting distribution gives the proportion of time the chain is expected to be in each state for a time interval and time period in the future. The limiting distribution is equal to the unique stationary distribution which exists when a Markov chain is irreducible and aperiodic. The limiting distribution is found by solving Equations 15 and 16.

$$\boldsymbol{\pi P} = \pi \tag{15}$$

$$\sum_{i \in S} \pi_i = 1 \tag{16}$$

where $\boldsymbol{\pi}$ is a row vector consisting of the proportion of time that the chain is in each state.

The model output can take two forms. One output form is the Markov system with the probabilities of each state and the transition in each iteration. This output format could be most useful for evaluating scenarios and assigning an acceptable risk and reward for design and operation strategies (e.g., preventative maintenance scheduling, participation in utility services). The other output form is a time domain demand profile that estimates the number of fills, amounts, rates, and arrival times at each interval in simulation time. This output format could be most useful for sensitivity studies conducted on station capabilities and impact on station economics.

5.3. Predictive Demand Model Results

Each of these types of outputs are presented here as sample results from the hydrogen station predictive demand model.

5.3.1 Sample Week Simulation, All Station Types

Figure 26 shows a sample modeled fill count as a function of the day of the week and hour for each of the station classes. As is characteristic of the random processes used to model hydrogen demand, each simulation results in a unique hydrogen demand profile. The fill count for the larger scale hydrogen stations is larger than the fill count for the smaller stations. There is some weekly periodicity, but each day of week has a similar trend in that the lowest use times are in the early and late hours of the day. Based on the real-world data for hydrogen fills, the fill distributions on Saturday and Sunday do not have the same underlying distribution as the weekdays, with lower mean fill counts per hour over the day compared to the weekdays. The gasoline filling trend does not show this same weekend difference to the weekdays; therefore, it is expected that hydrogen fills will approach the same daily distribution as gasoline as the demand increases. Each of these trends probabilistically models the effects that are evident in the large-scale measured datasets derived from NFCTEC data.

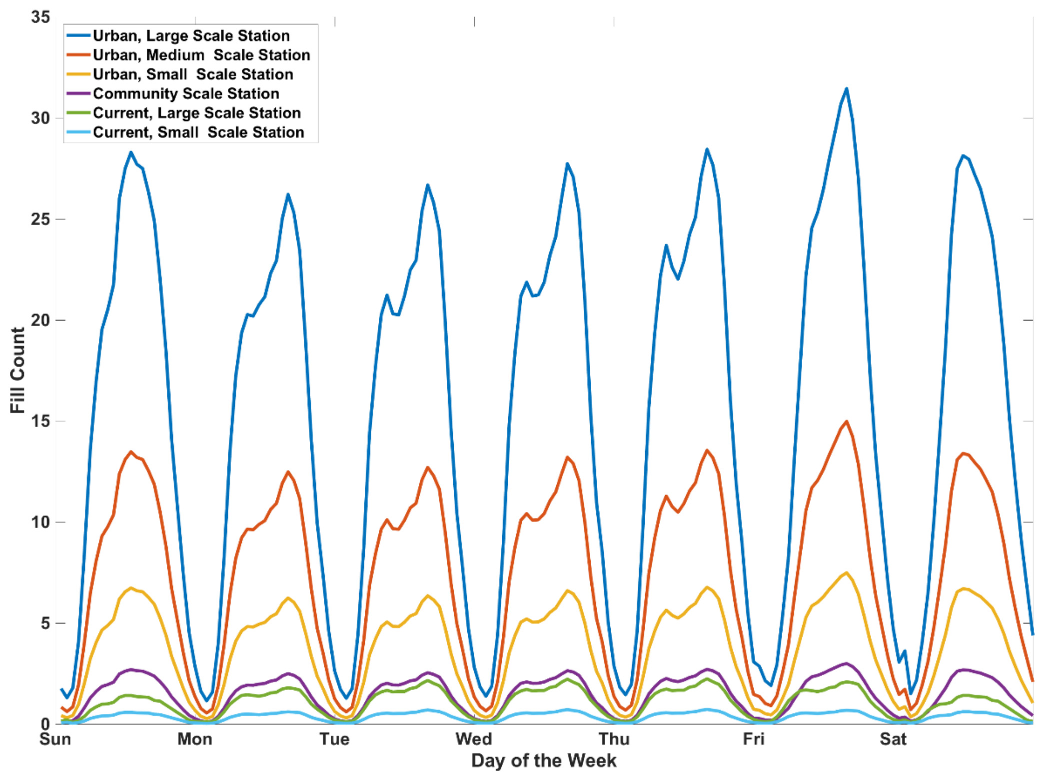

Figure 26. Modeled fill count for each station class over a 7-day time period, Sunday through Saturday

5.3.2 Mean Fill Estimates, Urban Medium Station Type

Statistical estimators are used to represent the hydrogen demand prediction. For example, Figure 27 illustrates estimates of the mean of key hydrogen demand parameters as a function of an hour of a particular day. The simulation data is filtered and binned based on day of the week and hour, as defined by the time period and interval selected as a user input. The maximum likelihood estimates are generated for each data segment and are based on a Poisson distribution for fill count, an exponential distribution for waiting times between fills, a normal distribution for fill rate, and the kernel density estimator for amount. Figure 27 provides examples from a Friday for the mean count, rate, and amounts by hour. Friday serves as a good example as it is normally a high-use day (as seen in Figure 26). The model has the capability to adapt and adjust these trained values as new data becomes available. New data, such as the number of FCEVs and the station count, availability, capacity, and configuration, is needed to keep this model segment relevant as the hydrogen market and technologies change.

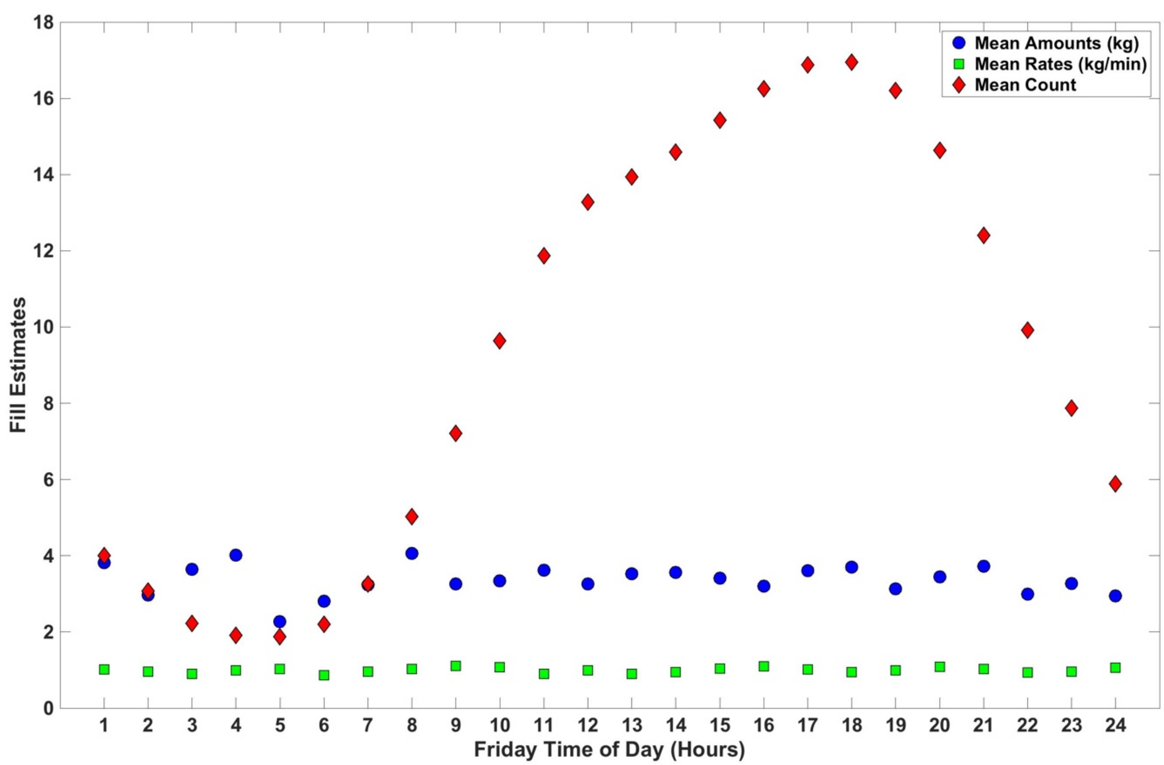

Figure 27. Mean rate (λ), fill amount, and rate estimates by hour for Friday, Urban Medium Station Type

5.3.3 Fill Count Probability, Urban Medium Station Type

The probability cumulative density function of fills, as described in Section 2.3, is shown in Figure 28. The probability is shown for 0 to 24 hours on a Friday, and for 0 to 28 fills in each hour-long time interval. A 50% cumulative probability limit (specified as a user input) is applied to estimate the number of fills in the time interval (Section 3.4). For instance, the model predicts 16 fills with a 50% cumualtive probability in the interval from 4 p.m. to 5 p.m. (1600 to 1700 hours).

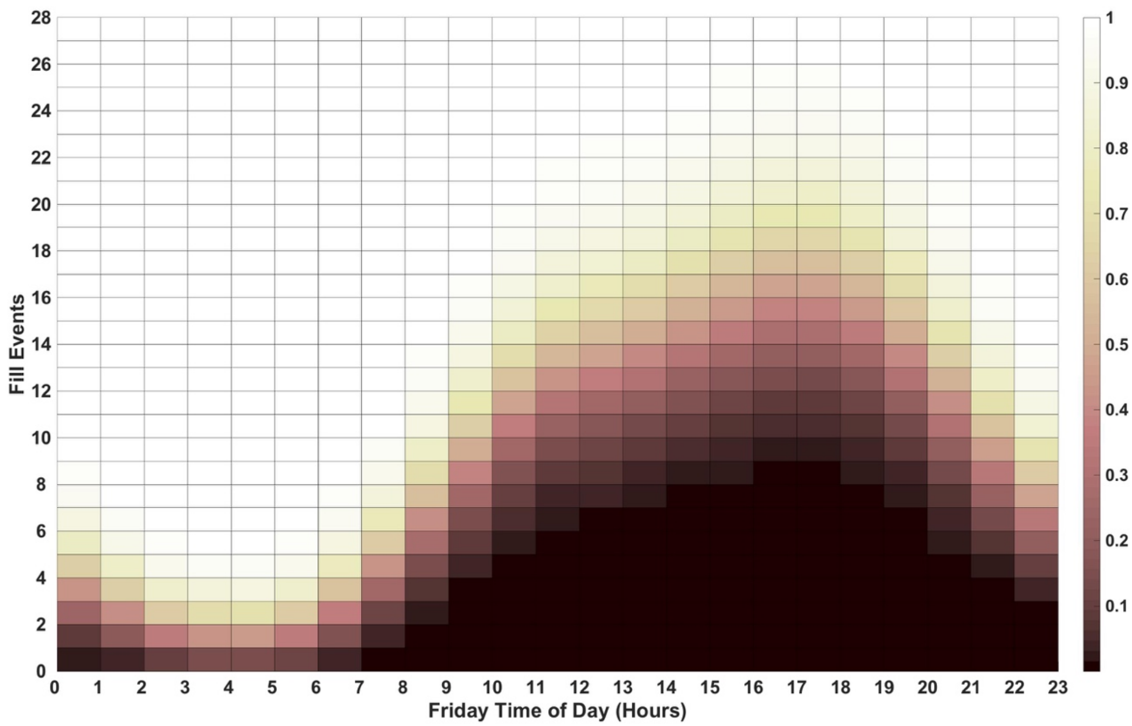

Figure 28. Fill cumulative probability map for a Friday, Urban Medium Station Type

5.3.4 Transition Matrix—Result Urban Medium Station Type

The transition matrix, with a discrete state space and time, varies for each observation period, n, which for this example is 1-hour intervals over 1-week period. This interval creates 168 transition matrices (one for each observation period). The probability of a fill changes based on the time of day and day of the week, so this is the basis for each transition matrix per observation period. The transition vector is square, using state A (available and standby) or state B (available and fueling). The wait time and filling times define the probability of the station state transitioning to either state A or B. Fills occur randomly following a Poisson process with filling times dependent on the two random variables, rates and amounts, over each 1-hour interval, which is further broken down by timesteps to estimate waiting times. Based on the timesteps, fills that elapse over the timestep is a transition from B-to-B. Likewise, a waiting time that elapses over the timestep is considered to be a transition from A-to-A. At any other point within each timestep, transitions will either be from A-to-B or B-to-A. A sequence is generated based on the simulated data and from that sequence of events, the probabilities of each transition is determined. At a minimum, the station state will switch to state A (available, standby) once the fill is completed, unless there is another fill immediately following. The transition matrix (Equation 17) is of the form,

$$\boldsymbol{P(n)} = \begin{bmatrix} P_{A,A}(n) & P_{A,B}(n) \\ P_{B,A}(n) & P_{B,B}(n) \end{bmatrix} \tag{17}$$

Where the first element represents the probability of a transition from state A back to state A, the second element ($P_{A,B}(n)$) represents the probability of a transition from state A to state B, and so on. The probability of a back-to-back fill is $P_{B,B}(n)$. Each row must sum to 1 and each state is discrete, that is, the station will not be available and fueling and also in standby simultaneously. The model assumes that the station has sufficient fueling positions to handle the demand. (The addition of fueling positions and queueing is expected to be important to the model for high-throughput demand scenarios.) Each observation period, *n*, has an associated probability vector (Equation 18) of the form,

$$\boldsymbol{\pi}^{(\boldsymbol{n})} = \begin{bmatrix} \pi_A & \pi_B \end{bmatrix} \tag{18}$$

We begin with an initial probability vector (Equation 19) that assumes the station is available and ready for fueling in (state A).

$$\boldsymbol{\pi}^{(\mathbf{0})} = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{19}$$

The limiting distribution for an hour interval, $\pi^{(n)}$, is computed by solving Equation 20,

$$\pi_j = \lim_{n \to \infty} P(X_n = j \mid X_0 = i), \ \forall\, i, j \ \in S \tag{20}$$

This is completed for the time period specified by the user (e.g., 7 days).

The procedure to create the fill demand results for 1-hour intervals over a week are as follows. The fill count is found based on the Y with at least 50% cumulative probability. Fill amounts and rates were randomly generated, as described in Section 2.4, and provided as an example Section 3.4. Table 7 is a subset of the station state estimation for two periods on a Friday, from 6 a.m. to 8 a.m. (0600 to 0800 hours) and from 2 p.m. to 8 p.m. (1400 to 2000 hours). These two periods were selected to provide a comparison between morning and afternoon, as well as using the busiest fueling period (Friday afternoon). The Urban Medium Station Type, the example type used in Section 5.3, is the middle column. Two other station types are provided to show how the transition states vary for different station classifications. For each 1-hour time interval, the transition matrices were generated as well as the limiting distribution which are represented in the table as the transpose of π (i.e. the first element is the proportion of time the station will spend in standby, the second element is the proportion of time spent fueling).

Table 7. Example Station Transition Matrix and Limiting Distribution, Three Station Types

			Max Current Station			Urban Medium Station			Urban Large Station		
			A	B		A	B		A	B	
Counter	Day, Hour		State Probability		Lim. Dist.	State Probability		Lim. Dist.	State Probability		Lim. Dist.
125	Friday, 600	A	1	0	1.00	0.48	0.52	0.53	0.47	0.53	0.53
		B	1	0	0.00	0.6	0.4	0.47	0.59	0.41	0.47
126	Friday, 700	A	0.49	0.51	0.54	0.46	0.54	0.53	0.35	0.65	0.55
		B	0.59	0.41	0.46	0.59	0.41	0.47	0.78	0.22	0.45
127	Friday, 800	A	0.49	0.51	0.53	0.45	0.55	0.51	0.4	0.6	0.50
		B	0.59	0.41	0.47	0.58	0.42	0.49	0.59	0.41	0.50
133	Friday, 1400	A	0.47	0.53	0.53	0.36	0.64	0.48	0.28	0.72	0.45
		B	0.59	0.41	0.47	0.59	0.41	0.52	0.6	0.4	0.55
134	Friday, 1500	A	0.48	0.52	0.53	0.31	0.69	0.50	0.26	0.74	0.45
		B	0.59	0.41	0.47	0.68	0.32	0.51	0.59	0.41	0.55
135	Friday, 1600	A	0.48	0.52	0.53	0.35	0.65	0.47	0.25	0.75	0.45
		B	0.59	0.41	0.47	0.58	0.42	0.53	0.61	0.39	0.55
136	Friday, 1700	A	0.37	0.63	0.59	0.3	0.7	0.49	0.24	0.76	0.44
		B	0.9	0.1	0.41	0.67	0.33	0.51	0.58	0.42	0.56
137	Friday, 1800	A	0.48	0.52	0.53	0.36	0.64	0.48	0.25	0.75	0.44
		B	0.59	0.41	0.47	0.58	0.42	0.52	0.58	0.42	0.56
138	Friday, 1900	A	0.48	0.52	0.53	0.35	0.65	0.48	0.25	0.75	0.44
		B	0.59	0.41	0.47	0.6	0.4	0.52	0.59	0.41	0.56
139	Friday, 2000	A	0.48	0.52	0.53	0.36	0.64	0.48	0.26	0.74	0.44
		B	0.59	0.41	0.47	0.59	0.41	0.52	0.59	0.41	0.56

As is illustrated in Table 7, most of the time is spent in state A, standby, for the Max Current Station type whereas the majority of time is spent in state B, fueling, for the Urban Large Station type. In the scenario when the station is consistently in state B, the addition of multiple fueling positions and application of queueing theory is particularly relevant and needed. The Urban Medium station is in state B more than half of the time, observed in the limiting distribution for a Friday between 1600 and 1700, with an estimated 31 minutes spent fueling. Higher demands, with more time in state B, suggests a future addition could be model for individual nozzles and queuing. The model currently allows for up to 4 fueling positions without assigning individual states per nozzle.

5.3.5 Fill Profile, Urban Medium Station Type

A demand profile can be general with probabilities for the different variables and time intervals, or the demand profile can be more specific, including estimated arrival times of vehicles for fueling. A time interval of 1 hour over 1 week could provide the right amount of visibility to determine storage needs and delivery schedules. Whereas a time interval of 5 minutes in 1 day could provide better insight into operating strategies and component sizing, especially when a station operator is balancing the performance and economics of a peak demand versus a base demand. The fill amounts and rates are randomly generated based on the mean and standard deviation of the training data set. The wait times, or time between fills, are used to generate fill start times to create a demand profile matrix (Table 8). The predicted fill profile for one week is shown in Figure 29.

Table 8. Fill Profile Example, Friday 1600 Hours, Urban Medium

Day ID	Fill Start, Hr	Fill Start, Min	Amount, kg	Rate, kg/min
6	16	0	3.5	1.0
6	16	1	3.2	0.8
6	16	2	4.1	0.9
6	16	6	3.2	0.9
6	16	7	3.0	1.0
6	16	9	2.0	1.2
6	16	12	1.8	1.1
6	16	14	2.3	1.2
6	16	17	2.2	1.2
6	16	19	3.1	0.8
6	16	21	3.4	1.1
6	16	29	3.2	1.3
6	16	29	3.1	0.9
6	16	29	3.6	0.7
6	16	30	3.7	0.8
6	16	31	3.4	0.8

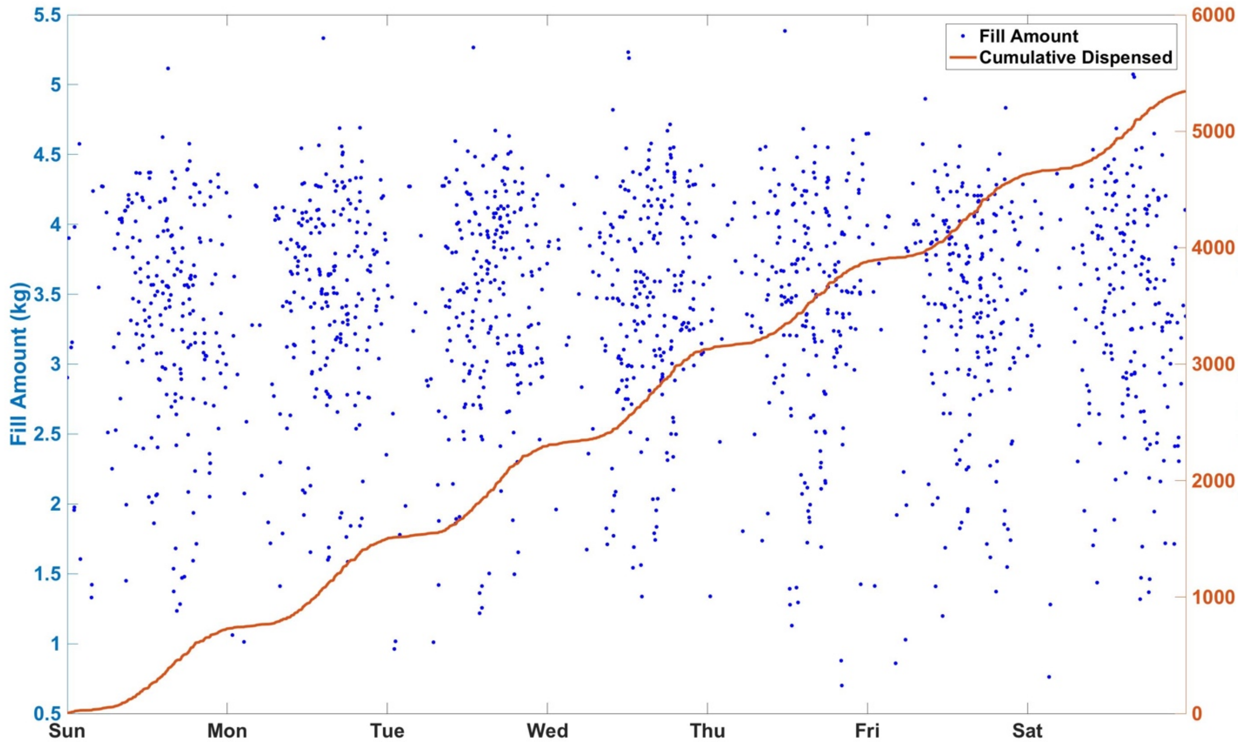

Figure 29. Weekly fill profile (fill amount is left y-axis and cumulative hydrogen dispensed is right y-axis) for Urban Medium Station Type

5.4. Applying the Predictive Hydrogen Demand Model

Hydrogen station design and operation is typically based on manufacturer models, economics, policy, and best practices learned from past stations. All of these inputs provide valuable insight and have been successful in the early demonstration and market phases. The fuel cell mobility market is evolving quickly, however, with more vehicles leased and sold, new deployment regions, and even new technologies (such as trucks) with drastically different fueling conditions and requirements. Changes like these indicate there is opportunity for improvements to improve station flexibility, performance and economics when implementing an adaptive, predictive hydrogen demand model.

5.4.1 Fueling Stations for Light-Duty Vehicles

A primary challenge for hydrogen infrastructure success is cost, including capital cost, hydrogen supply costs, supply chain costs, and O&M costs [133]. The costs challenge is magnified when a station has a low utilization. To be profitable, a hydrogen station operator requires high utilization so that operating costs can be spread across more hydrogen sales [34]. Although controlling demand is not feasible, there are a few ideas about how to lessen the impact of low utilization, especially in the early stage of commercialization [136].

An option that is enabled by this work is to integrate an adaptive hydrogen demand model into the station planning, controls, and operation processes. The proposed hydrogen model must evolve over time as conditions change (such as the number of FCEVs, station age, and availability) to improve station economics [137], [138], [139] without sacrificing performance for the station customers (e.g., FCEV drivers), but key ways that the hydrogen demand prediction model developed for this study could benefit the industry would be through:

- Station and equipment sizing: The size of station components influences station capital costs and capability, with the expectation that the station can sufficiently handle demand on both day 1 and in year 5. Predicting demand based on actual fill data and future predictions for FCEV deployment provides a tool for sensitivity studies on the impact of economics and capabilities when ensuring base- or peak-demand scenarios. Decisions made by the station operators on when, how, and what to upgrade also can be informed by a predictive demand model.
- Maintenance strategies: The reliability of hydrogen stations is a current challenge with regard to both frequency and cost [33]. By adding the station state of "unavailable" into the model, the station transition matrices and the reliability engineering best practices should enable business-based decisions that evaluate the economic impacts of when and what to maintain versus staying available for the high-value fueling.
- Operation strategies: Selling hydrogen is the primary function of a hydrogen station and the method of doing so ultimately dictates the consumer price. Station operation conditions such as when to compress, deliver, and chill, all impact the cost of dispensing hydrogen to vehicles and therefore station operation economics. The utilization of a predictive demand model can enable station operators to evaluate the impact of new operation strategies based on individual business models.

5.4.2 Application for Other Technologies Such as Buses and Trucks

Our demand model has been built using data derived from light-duty, passenger FCEV fueling. Many other technologies (for both fuel cells and batteries) that show promise, and the need for an alternative infrastructure for fuel other than gasoline also can benefit from this model. As new data becomes available, this model can be adapted for new station types such as a truck-stop type station, multi-use commercial station, and a hub such as an airport or marine port. The biggest hurdle to adapting the model to other demands is data availability. Currently underway are projects (e.g., DOT and California funded hydrogen stations, fuel cell bus, and fuel cell truck demonstrations) that have the potential to generate valuable training and validation data for the adaptation of the hydrogen, light-duty demand model to an alternative infrastructure demand model.

5.5. Conclusion

Gasoline stations and the required infrastructure are well established in the United States, with decades of legacy data to inform and optimize performance and economics. As hydrogen fueling stations grow to comparable size and capability of gasoline infrastructure, there is a need to understand the demand for hydrogen fueling for an informed and optimal scale-up process. Informed by a broad dataset of hydrogen fueling events, this study proposes a statistical model to predict the hour-by-hour demand for hydrogen fueling, as a function of variables such as hydrogen station type, size, location, time of day, and more. By comparing hydrogen to gasoline fueling datasets, his study demonstrates that the infrastructure supporting new mobility technologies can utilize gasoline fueling trends to inform decisions. The predictive hydrogen demand model that was developed for this study demonstrates the ability to model the station state (fueling or standby), estimates of fill count, amount, rate, arrival times, and time between fills. These results are valuable as inputs to station builders and operators who can make more informed decisions on requirements, future needs, operation, and maintenance strategies that directly impact the future and economics of hydrogen infrastructure.

The fueling demand model was trained with real-world station data, estimating the probability for future fill time, amount, frequency, and times, starting from the assumption that station fueling can be based on legacy hydrogen filling data and gasoline fill trends. A station operator will be able to customize station sizing and capability, as well as estimate ideal times (i.e., times during low use or low risk) for station maintenance or even to assess and incentivize fueling during particular times. An example is an assessment of station capability for current demand versus future demand, or the risk of expensive capital equipment versus future fueling revenue. When the station operator integrates the station capability with operating economics, maintenance decisions are driven by data so that revenue generation has minimal interruptions. Researchers are also able to utilize the predictive demand model for future scenario studies like integration of a hydrogen station with grid services, where future demand and station state of charge dictates whether the station is available for grid services.

Based on these expected benefits, the predictive demand model can improve economics of hydrogen station operation. Many factors influence the benefits of predicting demand, such as the deployment timeline for FCEVs and station availability. Therefore, benefits will be quantified with individual station operators and stations where implementation of the predicting demand model can be customized to an individual station's current output, capability, and projected FCEV deployment.

CHAPTER 6 – HYDROGEN STATION PROGNOSTICS HEALTH MANAGEMENT MODEL

6. Introduction to the Hydrogen Station PHM

Research Question 3 aims to identify an active hydrogen station health monitoring system that is actionable and effective at improving hydrogen station availability. Based on widely used reliability engineering methods and the low reliability of current stations, this research advances the hypothesis that a hydrogen station PHM could increase station availability by proactively managing maintenance in order to minimize unscheduled failures. Individual station operators are growing their experience and have specific strategies in development, yet there little to no published information on the application of reliability methods for station operation. A gap in available information and an observed challenge with station reliability, make this an ideal application to study a system-level PHM for hydrogen stations.

The observed reliability challenge can be seen in a high frequency of component failures [101]. The MFBF for the leading maintenance category (dispenser system) is less than 500. And a high number of failures results in high O&M costs, over $10,000 per station per calendar quarter, which is seen by hydrogen prices that are currently 4 to 5 times higher than parity with gasoline prices at the pump. Demand is expected to grow [96], which is likely to exacerbate the reliability challenge.

There is renewed momentum with supplier involvement [140], holistic hydrogen system solutions [1], [118], and commercially available and planned fuel cell vehicles [25], [26], [27], [105]. All this activity is pushing progress in lowering hydrogen production costs with aggressive targets for supply chain, utilization, and deployment. However, there is a gap in publicly available information addressing a near-term challenge of hydrogen station reliability. Hydrogen station reliability directly influences consumer acceptance of hydrogen technologies and can also be improved through the application of reliability engineering.

6.1. Hydrogen Station Status

Publicly available hydrogen fueling stations are essential for mass adoption of hydrogen fuel cell electric vehicles (FCEVs). Hydrogen-powered vehicles exhibit numerous benefits relative to conventional vehicles and other zero-emission vehicles [5], specifically related to their low life-cycle greenhouse gas emissions [6], [7], long range and fast fueling [8], competitive market price (with lease and purchase options) [9], [10], [11], and durability [12]. As the demand for hydrogen-fueled vehicles has increased with advancements in fuel cell vehicle technologies, the number and variety of hydrogen stations has increased accordingly [96].

The hydrogen fueling station capital investment costs, and the O&M costs make up a significant fraction of the cost of hydrogen delivered to vehicles. For instance, in the fourth quarter of 2018, the average maintenance cost per kilogram hydrogen dispensed was $1.30 [101], which is likely too high to meet the gasoline price parity target of less than $4 per kilogram. This estimate is based on the assumption that maintenance costs directly contribute to the dispensed hydrogen fuel price, but in many ways the non-monetized costs of hydrogen station maintenance—particularly unscheduled failures—are higher than the monetized cost of maintaining the fueling station.

When a hydrogen fueling station fails in its function to deliver hydrogen, this can have a detrimental effect on vehicle users' acceptance of hydrogen technology. For example, FCEV drivers fill up their vehicles when their tanks are 30% full on average [141]. This fueling behavior can be attributed in part to the range anxiety of electric vehicle drivers, which is different than gasoline vehicle fueling behavior [21], and is due in part to consumers' concern that the hydrogen station may not be available due to breakdown or unplanned maintenance [106]. Hydrogen station availability is so essential for consumers that both industry and government have developed software for real-time station availability status [87], [142]. At present, station operators are servicing hydrogen stations with dueling objectives. On one hand, they must service the system quickly to maintain the availability of the hydrogen station to meet consumers' reliability demands. On the other hand, they must take time to investigate the root cause of the failure to avoid future failures. The current frequency of hydrogen station component failures is too high—the MFBF for the leading maintenance category (dispenser system) is less than 500 [101]. This is approximately one failure every 15 days, based on current fueling trends, and is lower than the mean time between corrective maintenance activities of 21.5 days for gasoline stations in a "medium failure station" category [117].

Based on this understanding, there is a significant need to understand and improve the reliability of hydrogen fueling stations. This study seeks to apply reliability engineering concepts to hydrogen station O&M so as to reduce the cost of O&M and thereby reduce delivered hydrogen costs. This study presents the development of a hydrogen station prognostics health monitoring (H2S PHM) model. The H2S PHM model includes steps to identify the needed data, observe operation, analyze the condition, and decide on actions, if any. This modeling should enable a station operator to perform preventative maintenance instead of reactive maintenance to system failures, with real-time processing of information to predict failures and realize lower cost than conventional maintenance plans [143]. A primary value of PHM is that it can inform O&M strategies that balance technical function and economic business decisions. In order to do that, PHM estimates RUL to determine future component functionality and to economically evaluate a course of action [144].

6.2. Review of a Hydrogen Station and Reliability

6.2.1 Hydrogen Station Overview

A hydrogen station is a complicated system with numerous mechanical, electrical, chemical, safety, and structural subsystems. A hydrogen station must seamlessly and safely manage the delivery of high-pressure, nearly-cryogenic hydrogen across varying ambient and throughput conditions and provide a user interface that is safe for the general public (see Figure 30). There are numerous suppliers for hydrogen stations and their components, across the engineering specialties such as rotating equipment, cooling, pressure vessels and piping, safety, and electrical. Not all of the components are hydrogen-specific designs because the supply hasn't justified the development of hydrogen-specific subsystems. To date, hydrogen station evaluation projects [34], [69], [65], [123] have analyzed past events to study and report on station performance, economics, maintenance, and reliability. Through these projects, data is available to benchmark the challenge of reliability, along with targeted component reliability efforts [122], [120].

Figure 30. Fuel cell electric bus fueling at a hydrogen station (photo credit: NREL)

6.2.2 Reliability Engineering and PHM Overview

At present, the individual operators of hydrogen stations are improving the reliability of hydrogen station operation through station operation and repairing failures. The published literature does not reveal any comprehensive research on hydrogen station system-level reliability engineering, although there is demonstrated potential to improve station reliability and availability, based on existing reliability engineering literature and an assessment of the current hydrogen station reliability [145].

Reliability Engineering methods aimed at improving reliability, decreasing unforeseen failures, and lowering operational costs have been in development and are applied in many different industries [89]. For example, the U.S. Army Material Systems Analysis Activity (AMSAA) published an AMSAA Reliability Growth Guide [88] that summarized benefits of reliability growth management to be finding unforeseen deficiencies, designing improvements, reducing risk, and increasing probability of meeting objectives. Reliability engineering is commonly applied to rotating equipment [90], [91], and the wind industry is applying diagnostics and prognostics to improve wind farm reliability [92], [93], [146]. PHM, specifically, is also regularly applied to equipment and complicated systems to predict failure, as evident by many scholarly articles reviewing, researching, and applying prognostics and health management to engineering systems. Just a few examples of these systems include rotating equipment [147], wind turbines [144], fuel cells [143], batteries [148], and development of monitoring systems [149]. Sun et al. summarizes the benefits of PHM for system design, reliability prediction, logistics design, safety, quality control, extending service life, and cost [150].

Although there is no strong consensus on what the best methods for PHM modeling might be, or what metrics define success [151], there are some common classifications of methods (Figure 31), which are applicable to a hydrogen station. Generally, a PHM method is based on either a data-based, physics-based, or hybrid approach [152], [153]. Options for a data-driven model are historical failure data and empirical operation lifetime data. The data-driven model is typically a statistical model or an artificial intelligence model. Options for a physics-driven model are theoretical or empirical models, with numerous model options that are specific to the equipment function and operation being modeled. The hybrid model combines historical data, available component models, and future loading conditions with the intent of a more accurate model than an either-or model [154]. Section 6.3 will present PHM methods and propose options for application to hydrogen stations.

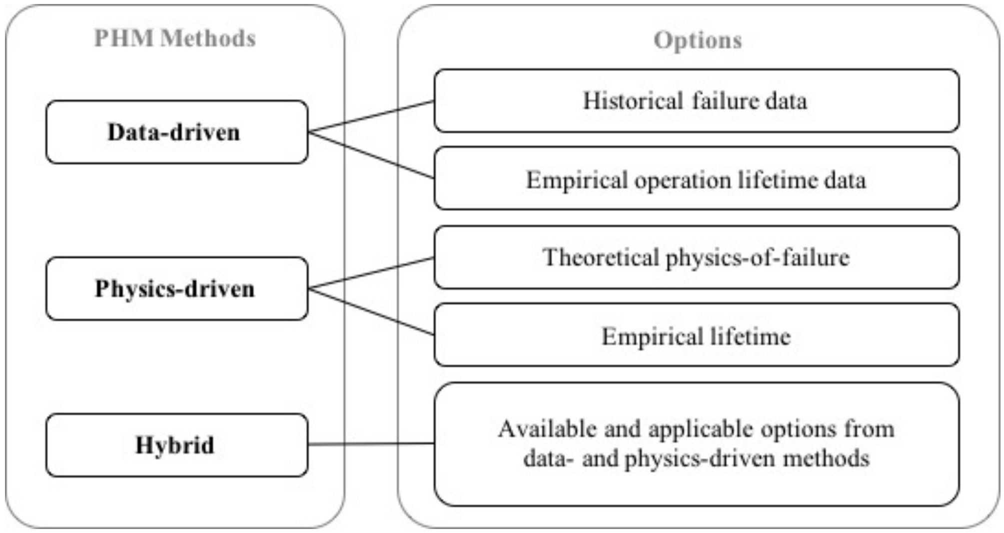

Figure 31. Summary of PHM methods and options

6.3. Hydrogen Station PHM Model Methods

With the overarching objective of improving the reliability costs of hydrogen stations, this section presents the methods for developing the H2S PHM, where stations have attributes that complicate the selection of PHM approaches to operational improvement. For instance, complicated systems, like a hydrogen station, can be difficult to operate and maintain especially when one small component can have a large impact on system operation and function. Another challenge is that there are mixed failure modes and the real-world failure data is noisy and uncontrolled for identification of failure modes. Understanding the interconnections within complicated systems requires sophisticated models capable of handling multiple data inputs, technical/human decision making, and an understanding of uncertainties [155]. These high-fidelity, validation-rich models do not yet exist for many of the equipment and systems in hydrogen stations. For example, hydrogen embrittlement is a well-known issue [156] and an active area for research to find low-cost materials and designs that are safe for hydrogen use. Material failures, such as crack growth, may be accelerated in a hydrogen environment especially in high-fatigue operating conditions. Therefore, a hybrid method is not yet feasible for the H2S PHM because there are not existing models of hydrogen balance of plant components based on the current operating conditions that includes hydrogen embrittlement issues, at high pressure (70 MPa) and cold gas temperatures (-40^{o}C).

The decision for which PHM method to use is based on what inputs are available. In this case, hydrogen station operation data is more readily available than physics-based hydrogen equipment models. In fact, we are in a unique situation because 30 stations operational in the U.S. regularly report O&M data that includes historical failure data and operation lifetime data. Therefore, a data-driven method is recommended for the H2S PHM at this initial stage, framed by a statistical regression model. The proposed Weibull statistical model (a well-established lifetime data analysis method) was selected instead of an artificial intelligence model because there was not enough, consistent data for the artificial intelligence inputs.

The proposed, data-driven, H2S PHM model has four main segments. The initial segment ("identify data") is added to the 3-part framework of Jouin et al., and includes development of instrumentation data, historical maintenance data, and data from model(s) [149]. The "observe" model segment includes data acquisition, data processing, and faults. The "model/analyze" segment includes condition assessment, diagnostics, and the calculation of prognostic metrics such as RUL. The final segment, termed "decide", includes decision support and human-machine interface that relies on technical expertise and understanding of the system. This architecture was used to break down the inputs and outputs of the H2S PHM model and defines means for implementation with hydrogen station operation to improve reliability. Each segment of the H2S PHM (shown in Figure 32) feeds information to other segments, including feeding new lessons back to the segments for improvements as more operation data and physics of failure modeling becomes available.

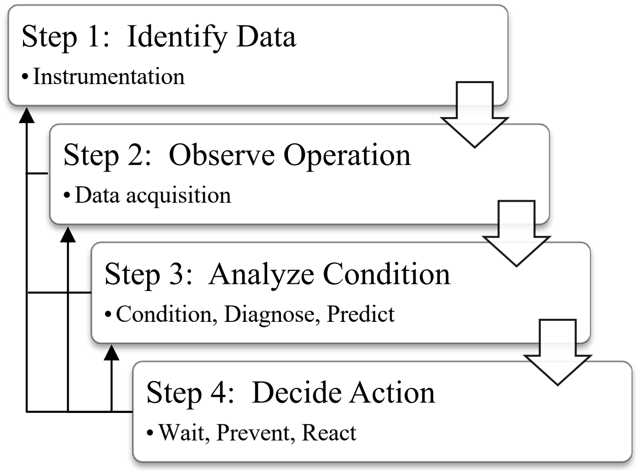

Figure 32. General H2S PHM model segments

6.3.1 Step 1: Identify Data

Datasets to inform the H2S PHM are available from the instrumentation used to control every hydrogen station. The subsystems with instrumentation are the hydrogen source (on-site production or delivery), compression, storage, dispensing (which includes chilling), and safety monitoring. These instruments are shown in the generic gaseous hydrogen station process and instrumentation diagram (P&ID), shown in Figure 33. This P&ID is simplified to show typical instrumentation on hydrogen stations without extensive details on the multiples of components like valves and storage [100].

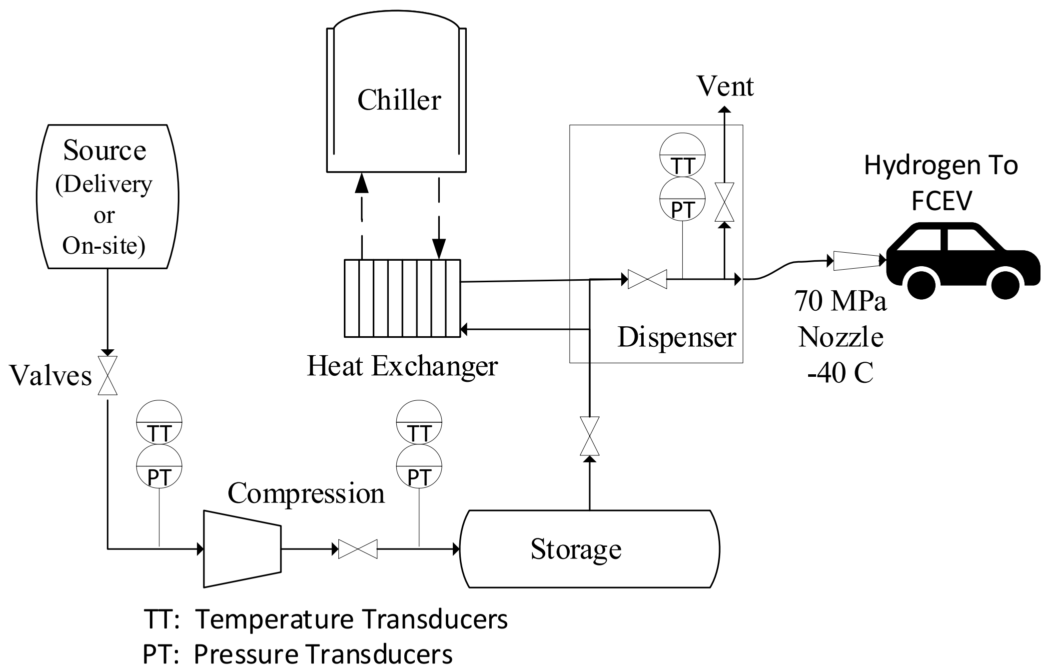

Figure 33. Simplified station (gaseous) P&ID diagram

The most common instrumentation in hydrogen stations measures gas pressure and temperature. Pressure is monitored upstream and downstream of compression and dispensing, as well as at the storage system. Temperature is monitored at the chiller and dispenser. Other measurements include cycle counts on the storage system (e.g., depletion/fill), valves, and dispenser (e.g., fill count). On-board vehicle storage tank temperature, pressure, and volume are also recorded during every fill with communication between the station and the FCEV. Table 9 lists component and subsystem measurements.

The frequency of data acquisition varies by signal and purpose. For instance, ambient temperature conditions and general station state information such as the quantity of stored hydrogen may be collected only once or twice a day. Other instrumentation could be stored every second while that subsystem is operating (e.g., high-pressure compression) or during a fill (e.g., dispenser gas temperature). Instrumentation for data acquisition contributes to capital and O&M

costs, so not all instrumentation will be available for PHM purposes, especially given the capital and O&M cost challenges of hydrogen infrastructure that were discussed in Chapter 1. A clear benefit must be demonstrated in order to justify additional costs for system instrumentation.

Table 9. Preferred measurements by hydrogen station part for purposes of the H2S PHM

Part	***Function/Tag***	***Measurement(s)***
Valves	Open/close valves	Open/close cycles, temperature (fluid and ambient), pressure, MFBF, valve position
Control valves	Control flow	Adjustment cycles, temperature (fluid and ambient), pressure, MFBF, valve position
Compressors	Compress to storage tanks (up to ~87 MPa)	Operation time, pressure (inlet/outlet), vibration, MFBF, ambient temperature, variable speed
Chiller	Cool hydrogen prior to fill	Operation time, pressure, MFBF, ambient temperature, operation set point, solar gain
Storage	Low-, medium-, and high-pressure hydrogen storage	State of charge, discharge cycle, discharge amount, ambient temperature, MFBF
Sensors	Temperature, pressure, leak	Operation time, ambient temperature, measurement output (sensor dependent), MFBF

6.3.2 Step 2: Observe Operation

The station observation data stream for this study is based on two different sources of data: real-world hydrogen station data supplied by 34 stations across the U.S. to NREL's NFCTEC, and research data collected at NREL's HITRF.

This first data stream, real-world station data, includes data collected at every fill, at every maintenance event, and at every time when the station transitions from available to unavailable for fill (and vice versa). At every fill, the stations report date, time, amount, rate, vehicle starting pressure, and vehicle ending pressure (example shown in Table 10). At every scheduled and unscheduled maintenance event, maintenance data for is collected and tracked by component, subsystem, date, type, and action (example shown in

Table 11). At every available/not available transition, the stations report time, date and available/not available status through a Station Operating Status [87]. A limitation of this dataset is that it typically does not include second-by-second data for temperatures, pressures, and storage state of charge, or root-cause failure findings. Ideally for PHM purposes, assignment of all known component conditions prior to, or at, failure would be known and tracked for all maintenance events and equipment. In addition, typical parameters that contribute to failures are thermal, mechanical, chemical, physical, and electrical [157] should, ideally, be tracked.

Table 10. Retail hydrogen station sample fill data

Date	Amount (kg)	Rate (kg/min)	Starting Pressure (MPa)	Ending Pressure (MPa)
1/4/2018 9:03 am	3.1	0.83	28	70
1/4/2018 9:42 am	2	0.85	35	71
1/4/2018 10:39 am	3.7	0.83	21	70
1/4/2018 10:57 am	3.2	0.83	17	70

Table 11. Retail hydrogen station sample maintenance data

Date	Category (system, subsystem)	Action	Duration (hours)	Cause/Effect	Mode
2/3/2018 4:43 pm	Compression, Compressor	Replace	8	Pressure loss, warning high	Failed part
3/28/2018 9:00 am	Dispense, Valve	Replace	1	Failed part, hydrogen leak	Failed part
3/28/2018 9:00 am	Dispense, Dispenser	Upgrade	1	NA, NA	Upgrade
4/9/2018 1:00 pm	Compression, Compressor	Repair	2	Communication error, lost functionality	Adjustment

The second data stream, research data, is from NREL's HITRF, an exemplar, highly instrumented hydrogen station on campus at NREL. HITRF has the level of data acquisition that could support more detailed causal analysis (Table 12), but it is operated for experimental purposes that often do not match the operational conditions of retail hydrogen stations.

By using both of these datasets together, we can understand the potential for improvement of hydrogen station PHM through the proposed methods.

Table 12. HITRF station sample fill data

Date	Amount (kg)	Rate (kg/min)	Starting Pressure (MPa)	Ending Pressure (MPa)	Dispensing Temperature (°C)	Dispensing Pressure (MPa)
1/4/2018 9:03:26 am	3.9	0.83	28	70		
1/4/2018 9:42:16 am	Fill in progress	Fill in progress	35	Fill in progress	-10	35
1/4/2018 9:42:17 am	Fill in progress	Fill in progress	35	Fill in progress	-12	35.3
1/4/2018 9:42:18 am	Fill in progress	Fill in progress	35	Fill in progress	-15	35.6

6.3.3 Step 3: Analyze Condition

The goal of PHM development is to move from reactive maintenance (i.e., unscheduled) after a failure occurs to preventative maintenance (i.e., condition-based), scheduled to not negatively impact customers who want to fuel their vehicle. Condition-based maintenance doesn't wait until a component fails for repair or replacement. The component is proactively replaced during a preventative maintenance event when the specified component condition (e.g., cycle count) is reached and before the component fails [158]. Condition-based maintenance, in the context of hydrogen stations, may be the practice of a repair/replace event at a certain fill count or time in operation. An issue this with this limited practice is that it doesn't factor in the probability of failure so O&M costs may increase if the repair/replace event is completed too early. It is expected that this proposed analysis will improve condition-based maintenance strategy with enhanced data-detail regarding the survival rates by subsystem/component and expected RUL, using a statistical model from real-world data.

This recommended statistical analysis method assumes that the subsystem/component combination is the smallest model block for assessment and the aging parameter is the fill count and not the number of operation hours or days. There are many common parts (e.g., valves) across the subsystems yet each subsystem has significantly different operating conditions that are expected to influence the current condition and estimation for RUL (e.g., gas temperature at the storage system is approximately equal to the ambient temperature and gas temperature at the dispensing system is approximately -40°C). The fill count was chosen as the aging parameter because it has not yet been determined that station subsystems/components deteriorate simply based on time. The system is basically a closed system, except for possible small hydrogen leaks to the environment, and operation is almost entirely controlled by the request to fill.

Fill data by subsystem/component is required for this method and this data is generally two types: complete run-to-failure data or incomplete failure data from field systems. The complete run-to-failure data is preferred because it is controlled and thorough. This is not yet publicly available for the hydrogen station subsystems and components included in this study. Run-to-failure for hydrogen equipment is an active area of research however, with more data expected in the next 1–2 years [122]. Over time this will become valuable data to include into the analysis; in the meantime, the most extensive data available is incomplete failure data from retail hydrogen stations. Until then, the H2S PHM analysis data input is this incomplete failure data from real-world station O&M. The incomplete failure data will be analyzed with a traditional lifetime data analysis, or Weibull [108], [159] method. The traditional, three-parameter Weibull distribution function is shown in Equation 21.

$$F(t) = 1 - \exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{21}$$

where α is the scale parameter, β is the shape parameter, τ is the location parameter, and t is the aging parameter. A combination of α and β is sometimes represented as a combined parameter, $\lambda = \alpha^{-\beta}$. The Weibull distribution probability density function is shown in Equation 22.

$$f(t) = \beta\alpha^{-\beta}(t-\tau)^{\beta-1}\exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{22}$$

The available failure data will allow the model to extract key features ($\alpha, \beta,$ and τ) to assign the component condition and predict RUL. With the key features, the Weibull survival function, or reliability function (Equation 23), provides the probability that the component will successfully operate at time t.

$$R(t) = 1 - F(t) = \exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{23}$$

The conditional survival function is shown in Equation 24, where the survival is calculated at time t based on the successful accumulation of operation time T. The component will be assessed (green, yellow, red) based on the conditional survival function (Equation 24), as shown in the sample diagram (Figure 34). The model will assign an approximate condition that is simply a basic assessment of the component survival probability to complete the next fill, while acknowledging that the component has survived through T [160].

$$R\big((t|T)\big) = \frac{R(T+t)}{R(T)} = \exp\left[-\left(\left(\frac{T+t-\tau}{\alpha}\right)^{\beta} - \left(\frac{T-\tau}{\alpha}\right)^{\beta}\right)\right] \tag{24}$$

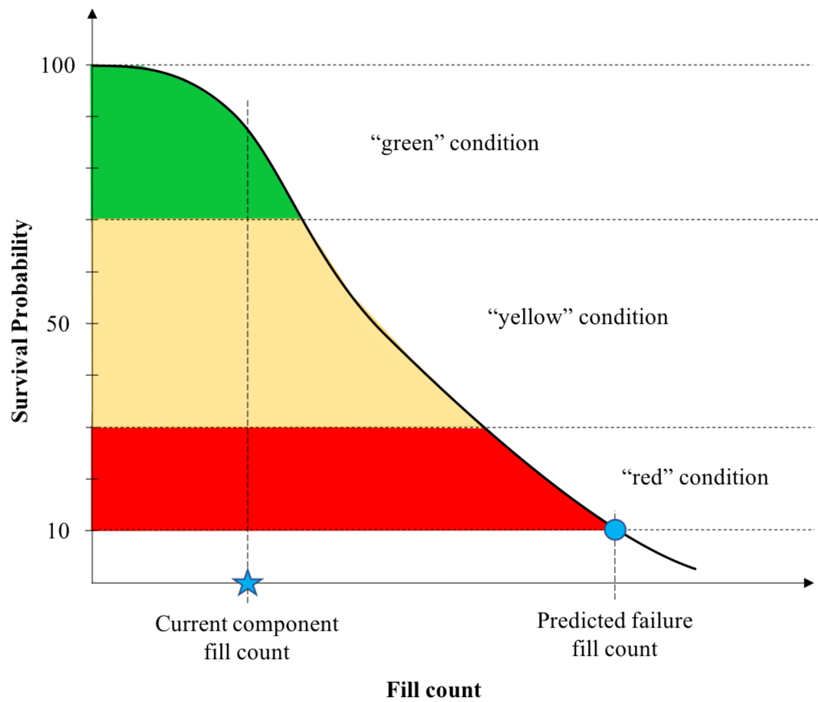

Figure 34. Placeholder for example survival function estimate (excludes infant mortality failures)

Weibull distribution data can be plotted against t, especially for complete run-to-failure data. In the scenario of incomplete failure data from retail hydrogen stations, the Weibull hazard rate (or failure rate in Equation 25) is recommended with the Weibull distribution data plotted against the cumulated hazard rate (Equation 26).

$$h(t) = \frac{f(t)}{\mathrm{R}(t)} = \frac{\beta}{\alpha}\left(\frac{t-\tau}{\alpha}\right)^{\beta-1} \tag{25}$$

$$H(t) = -\log\ \mathrm{R}(t) = \left(\frac{t-\tau}{\alpha}\right)^{\beta} \tag{26}$$

The last step is to estimate RUL (Equation 27).

$$RUL = T_{eol} - T \tag{27}$$

where T_{eol} (depicted in Figure 34 as "predicted failure fill count"), or the end-of-life, is the fill count at 10% survival probability, which is considered the failure point for the purpose of this analysis and T is the current fill count, or a potential failure point. Another way to look at this is as a health indicator (i.e., survival probability), tracking the delta between the failure and the latest observation [161]. Note, the predicted failure fill count is a subjective threshold that should be updated with additional failure data, root-cause failure results, and physics-based models to inform the precursors to component failure.

There are a few limitations with this analysis method, as described. For instance, catastrophic (or sudden) failures are not expected be predicted in this analysis. The method is only as good as the available data, which is varied in source, frequency, and fidelity. The proposed method does not include physics-based failure models as thresholds and times to wear-out failures are not yet known. The model uncertainty is not yet understood and should be included in future work with the comparison predicted with actual time to failure should consider not only the aging parameters but also the operating conditions. This proposed model sets the statistical framework which can be adapted and learn from additional data and include operating conditions or factors leading to failure as more root-cause failure data and physics-based models are available.

6.3.4 Step 4: Decide Action

The last step in the model is the presentation of information so that the station operator can make a data-driven decision (technical and economical) regarding O&M decisions and strategies. This step assumes that the conditional survival function and RUL will inform the operator, not automatically trigger an action, because at this early phase in commercial hydrogen station deployment, there is too much uncertainty in the statistical model. Implementing the H2S PHM model at this early stage is advantageous though because the model can be validated and iterated on in parallel to the station technology development and deployment, allowing for a validated model ready in future commercialization phases.

Along with the H2S PHM outputs, the station operator will rely on other inputs such as technician availability and economic impact, to determine the preferred actions, or no action at all. There is some guidance in the literature on assigning economic value to the decision to maintain or wait [144]. For example, the economic trade-off includes cost avoidance (replace/repair costs of preventative and reactive maintenance as well as downtime penalty costs) and generated revenue. Cost avoidance is the difference between the cost of an unscheduled (failed) maintenance event and the cost of preventative maintenance per the recommendation of the H2S PHM or prior to a failure. There is value in a "wait-to-maintain" option and this value is dynamic, as both the predicted and actual end-of-life will change due to operation (or other aging parameters like calendar time), discrete maintenance intervals based on the logistics (scheduling maintenance technicians and part availability), risk tolerance, and model uncertainties.

An optimizer for the value of completing maintenance, with the input and decision power of trained/skilled hydrogen station operators, could be developed in future work to evaluate the real impact on the day-to-day hydrogen station O&M costs. In addition, preventative maintenance planning based on a reliability centered maintenance method [162] can be improved with additional logic like whether an overhaul is possible or a repair is needed and if a function test is needed for further diagnostics.

6.4. Hydrogen Station PHM Model Results

The proposed H2S PHM model is an initial framework based on currently available data, with the intention that the model will adapt with future data and technology advances. This is important because leading categories for station maintenance may change as reliability improvements are implemented at stations, new technologies are introduced, and early system development failures are designed out with experience and lessons learned. To demonstrate the initial framework and the iterations, Figure 35, shows a general H2S PHM state diagram with the station O&M states (shown in black outline) integrated with the H2S PHM model steps (shown in green outline).

As a starting point, the station is initiated in a ready position and then is able or unavailable to fill. If the station is available to fill, then the station state will move to the "Fill" state when requested. The fill is either successful, with data sent to the H2S PHM "Observe Operation" state, or unsuccessful, in which case the station moves into an "Unscheduled Maintenance" state. This state also supplies data to the H2S PHM "Observe Operation" state and the station may be unavailable for a period of time, depending on the issue. Another O&M state is "Preventative Maintenance," where the station may or may not be ready and able to fill, depending on the specific preventative maintenance event. This state is scheduled and also provides data to the H2S PHM model. The "Identify Data" state (described in Section 6.3.1) identifies what data signals are needed. The "Observe Operation" state (described in Section 6.3.2) uses all data inputs to inform the "Analyze Operation" state (described in Section 6.3.3). The last state in the model is the "Decide Action" state (described in Section 6.3.4).

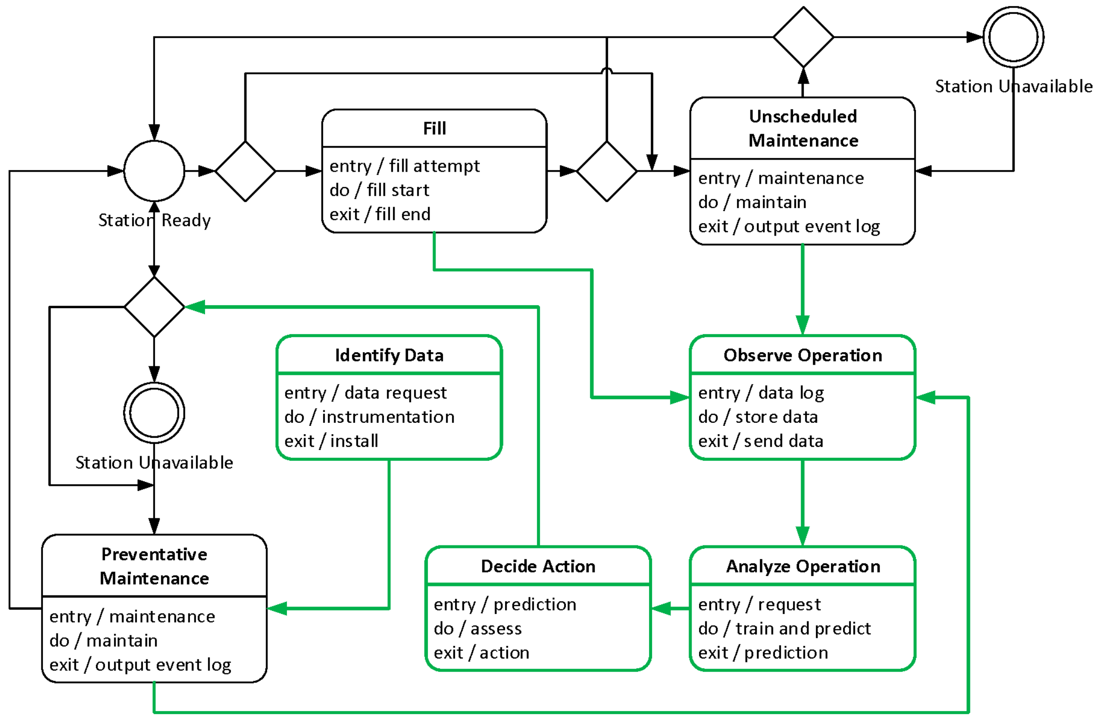

Figure 35. H2S PHM state model

6.4.1 Step 1: Identify Data

Available data for retail hydrogen stations is based on the NFCTEC O&M data template [34]. The NFCTEC data includes logs of hydrogen production, delivery, dispensing, costs, and second-by-second fueling data and maintenance/safety events. Heavily instrumented hydrogen stations (i.e., NREL's HITRF or Cal State Los Angeles's Hydrogen Research and Fueling Facility) can serve as a test bed for new hydrogen infrastructure instrumentation and precursors of component failures. This is expected for future study on the need and justification of additional instrumentation for an accurate and consistent set of failure data.

6.4.2 Step 2: Observe Operation

The primary data source is the retail hydrogen station data, with more than 465,000 hydrogen fills from more than 30 stations. Station operators typically supply new data every 1-3 months for NFCTEC analysis and reporting so this data could be used to update the H2S PHM regularly. The NFCTEC hydrogen station maintenance analysis shows that the dispenser, compressor, and chiller account for 90% of over 5,600 maintenance events. Therefore, these subsystems are the top priority for observation. Fittings and valves are common failure points within these subsystems, where failures often result in lost functionality and warning alarms. This highlights a challenge with the data-driven PHM approach, where failure root cause and operation conditions are not often found in the station maintenance records because the goal is generally to get the station fixed as quickly as possible, and the effects (e.g., a hydrogen leak or an alarm warning) do not often point to a failure cause (e.g., vibration, installation error, or material degradation).

The observation continues, with the knowledge of this data gap, and correlates the number of fills to each maintenance event, assuming that a component is considered new up until the first time it is maintained. The condition after that maintenance event is then dependent on the specific action like inspect, repair, or replace. Individual component tag numbers are not in the current data, so the components are grouped by function (Table 9) and subsystem. Other gaps in the existing data include individual component identification, gas pressure and temperature cycles, and ambient temperature cycles. These data are captured in the research dataset from HITRF and indicate that there are possible trends that could signal an impending failure. This is another area for future study.

6.4.3 Step 3: Analyze Condition

The training data is from all relevant retail hydrogen station data at NFCTEC, which introduces a problem of mixing different station configurations and failure modes. This data is the best available however, so all data is categorized by subsystem and components. Stations do have various suppliers, operating conditions, designs, and utilization rates yet all have similar functional subsystems and components (like a dispenser with valves and nozzles). Ideally failure modes and individual stations will be separated as more data is available and as the market continues to develop. Data from all stations are aggregated in this initial version to generate a shape and scale parameter for each subsystem/component category because of this common functionality. An expected advantage of using the H2S PHM at this early stage is that the aggregated statistics are a basis for comparison and iteration for station technology development, when there is insufficient data for the ideal scenario.

With the aggregated reliability analysis of all applicable maintenance data (i.e., unscheduled maintenance), the parameters are found by fitting the maintenance data in the H2S PHM Step 2, as described Section 6.3.3. An example of these parameters from fitting the aggregated and categorized maintenance data, using a 2-parameter Weibull distribution (assuming $\tau = 0$) is shown in Table 13.

Table 13. Example subsystem and component RUL estimates (not real data)

Subsystem	Component	Shape Parameter	Scale Parameters
Dispenser	Valve	0.58	32.8
Dispenser	Nozzle	0.66	830.8
Dispenser	Fitting	0.85	2851.0
Dispenser	Dispenser	0.62	2218.8
Compressor	Compressor	0.55	2414.6
Compressor	Valve	0.57	1362.5
Chiller	Chiller	0.43	1299.1
Chiller	Heat Exchanger	0.73	1361.6

The shape and scale parameter are determined from the aggregated maintenance data, but the RUL estimate is completed for an individual subsystem/component at a specific time for a station. Let us use the hypothetical example of a dispenser valve completing $T = 92$ fills without a failure. The H2S PHM model first calculates the conditional survivability function, which estimates the probability that the component will continue operating without a failure, with the benefit of knowing that the component has already completed T fills. Figure 36 has both the survival function and the conditional survival function for comparison in this hypothetical example. The difference in the blue and orange lines show the increase in probability for a component that has completed 92 fills (blue line) instead of a component that has not completed any fills (orange line).

The initial end-of-life criteria is a survivability probability of 10%. As noted earlier, this criterion should be updated based learnings comparing the actual failures with predicted failures, the economic trade-off of wait-to-maintain and the acceptable level of risk from individual station operators. In this hypothetical example, the $T_{eol} = 403$ fills and the RUL is 193 fills, based on the shape and scale parameters in Table 13.

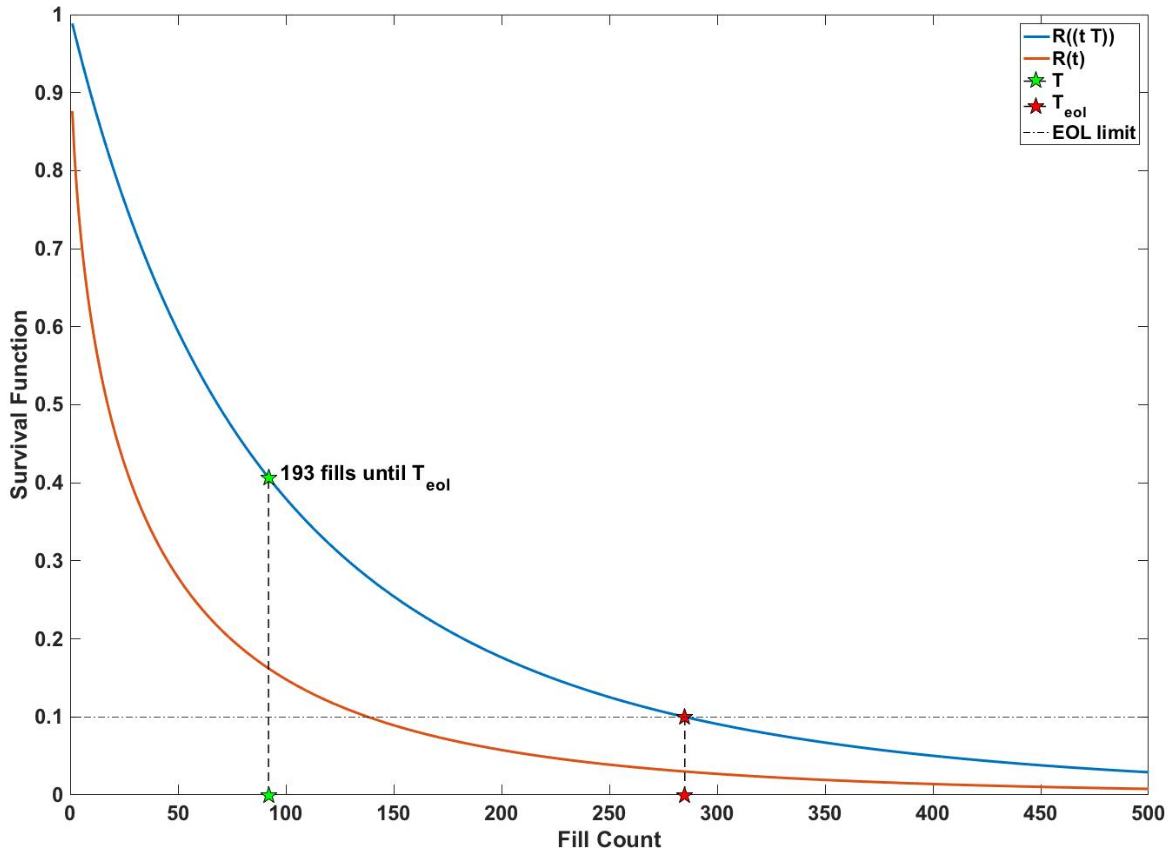

Figure 36. Sample RUL estimate for a dispenser valve

6.4.4 Step 4: Decide Action

When requested by the station operator, the H2S PHM estimates a RUL for each of the priority subsystem/components based on their real-time condition. Combining the RUL with other decision factors like technician availability, part availability, predicted future fueling demand, and economics trade-offs, supports the O&M decisions like when to perform maintenance, order parts, or continue active monitoring.

Continuing with the hypothetical dispenser valve example, let us consider a longer period of approximately 1 month, or 3,200 fills for a station averaging 2,500 kg/week. The RUL changes as fills are completed until failure or pro-active repair/replacement of the component. Figure 37 shows an example of how the RUL estimate changes over fill counts for the dispenser valve. This simple example has two scenarios for the same component. One scenario does not have a PHM (black dashed lines) and the other scenario with the H2S PHM (blue lines).

In the scenario without PHM, the dispenser valve fails and is replaced with an assumed station downtime of 3 times the median labor repair hours [101]. This multiplier captures the time margin that would be necessary for maintenance logistics like notification, part availability, and technician availability. The downtime (assumed constant for each reactive maintenance event and is captured when RUL = 0) is translated to the number of fills based on the predicted demand so that the number of fills varies based on the failure day and time of day. Note in this example the valve fails and is repaired at exactly the same fill count each time (identified by the black circle). This is used for illustrative purposes only and is not intended to state that the failure is known and repeated exactly.

In the scenario with the H2S PHM, the dispenser valve is replaced at different intervals (identified by the blue *). These illustrative replacement intervals show one possible path of utilizing the H2S PHM with different repair criteria as more is learned and uncertainty is reduced in predicting the RUL. For example, at the cumulative fill count of 1,346, the valve is on its third replacement cycle, with 382 fills on the current valve. At this point of maintenance, the RUL estimate is 54 fills, so the replacement may have been too early, but the next replacement cycle is completed with a RUL less than 50 fills. This simplified example assumes the H2S PHM model shape and scale parameters are consistent therefore the RUL estimate is repeated with each repair cycle. In an actual implementation, the parameters may be updated regularly in order to incorporate learning and comparisons from the actual failures and predicted failures.

Over the cumulative fills in this example, the H2S PHM value estimate is trending higher than the No PHM scenario, showing the potential that the H2S PHM is economically advantageous compared with the status quo maintenance method. This is primarily due to decreasing the station downtime and lower maintenance costs, however it does not take into account all the costs and influencing factors. Note that this is an overly simplified example meant to illustrate the factors influencing the decision step and what actions are taken. Future research is needed for an assessment on the return of investment of the H2S PHM and economic optimization that considers a full range of avoided O&M costs, revenue gain, and the PHM investment [163]. In its initial iteration, the H2S PHM may provide the most value in providing one more data source for the station operator's goal of high station availability but it is not yet ready for the full economic analysis as more data is needed for key variables like downtime per maintenance event and subsystem/category.

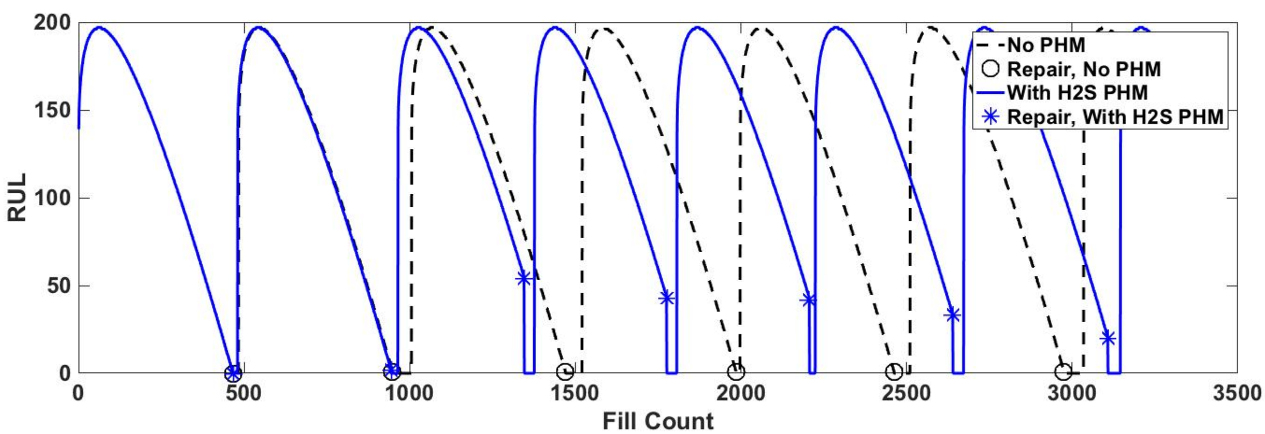

Figure 37. Time-series RUL example with variable repair schedules

An economic study of hydrogen fueling revenue, cost avoidance, and H2S PHM return on investment is suggested for future study. For example, the cost of unscheduled maintenance for today's hydrogen station is $1.30/kg [101] on average. The cost of PHM maintenance could be 30% of the unscheduled maintenance costs, based on an engineering estimate informed by other industry estimates [164], [165]. The maintenance cost in the H2S PHM scenario is lower because maintenance can be scheduled, and the station is unavailable for less time than the base scenario. Once the RUL is less than a low limit specific to the station operator, then the cost of preventative maintenance could be assumed to be the same as the cost for unscheduled maintenance and the cost avoidance is zero. A critical data stream for this economic study is station maintenance costs by subsystem/component for both planned and unscheduled maintenance.

6.5. Discussion

The H2S PHM model presented here is a proposed framework meant to avoid frequent, unscheduled maintenance events that are costly and negatively impact the customer trust in receiving hydrogen when it is needed. This model is entirely data-driven because physics-based models are not yet available for the components and subsystems operating in a hydrogen environment, which can have unique influences on failures like crack growth for steels, especially under stress [156].

The statistical model is constructed from incomplete failure data, without individual component identification (like a tag number) because the data supplied to NFCTEC doesn't include that level of detail. Implementation of the H2S PHM may be most effective with individual station operators because details like the component tag numbers and specific configuration would be available. In this case, the individual components can be tracked by tag numbers, failure frequency, repair times, and costs that should enable a more meaningful interpretation of the Weibull distribution parameters and maintenance economics than with the generic parameters used for this study. For the purpose of illustrating how a station operator may use the H2S PHM model, two hypothetical examples are provided below.

1. Valve replacement scheduling: a dispenser valve has a condition assignment of "yellow" indicating that this valve is close to the lower threshold for survival probability. The

yellow status highlights that the operator should monitor this closely and be prepared for maintenance. The station operator reviews this with the predicted fill demand over the RUL estimate. The operator also factors in logistical items like technician and part availability. The station operator then determines the best time for replacement based on all these considerations, ultimately minimizing the negative impact on the customers. If the valve replacement is scheduled, the total station downtime may be short because the station is only unavailable while the technician is actively working on the replacement. If the valve fails, the station may be down for longer because a technician needs to arrive to the site and make an assessment on the action required, and the action may not be possible if the part(s) are not readily available. The RUL estimate is valuable because it helps to balance the best time to do the repair/replace so that costs aren't incurred repairing a fully functional part and that a revenue is not lost due to an unscheduled failure.

2. Major equipment overhaul: Let us assume that a compressor overhaul would require the entire station to be unavailable for at least a full day. This is expensive and labor intensive, so it does not make economic sense to complete this maintenance too early in the operation life. The RUL estimate can be used to decide on the optimal time to complete the overhaul. This will also allow the station operator to mitigate any revenue or customer relationship risk with forewarning and other methods like pushing the station storage state of charge to 100% before the overhaul. The primary difference with this scenario and a basic maintenance practice is that the RUL estimate informs the timing decision. A major component like a compressor is also an ideal candidate for integrating

early warning signs (e.g., operation pressures), the statistical survival prediction, and a physics-based failure model.

In both of these hypothetical examples, uncertainty may limit the H2S PHM model's usefulness. In an early market phase, infant mortality failures may be difficult to predict and therefore the operator may not be confident in the RUL estimate. Any action initiated from the H2S PHM model outputs will also be influenced by uncertainty in the predicted fill demand and economic value. Another factor influencing uncertainty is whether the failures are systemic or simply because the market is new. For instance, a particular component failure may only be an issue because the component has not been customized for the hydrogen environment; when the supply chain is more established than currently, the component will be replaced with a customized with fewer failures and different failure modes.

As expected, when proposing a new method, there are a number of opportunities for improvements. Another future consideration is to study the assumption of a continuous failure model. If the behavior is discrete instead of continuous, the observations from the continuous model may be inaccurate [113]. Information from field data and continued study of the modeling will support the assessment of the data type and failures like burn-in or wear-out. If the continued study of the hazard rates shows variations in the traditional bathtub curve, the model should be adapted [112], [114], [166], [167]. The model may be also be customized as failure mechanisms are identified and used to inform the component condition as not all components may follow the typical aging phases as the traditional bathtub curve [168].

The number of variations and influences on the uncertainty are an indication that the H2S PHM is not be ready to be the prime source for O&M strategies. However, implementing the H2S PHM at this early stage can be beneficial because the model can have time for validation, additional training data, as well as develop in parallel to the understanding of failure modes, and station operator insight. From over 465,000 fills, the data is the most extensive data available from multiple station operators, configurations, and operating conditions. There is tremendous opportunity is mine these data, even with the limitations, for advancing next generation systems.

6.6. Conclusion

Currently, hydrogen station O&M is primarily reactive, which is reasonable in this early stage of commercial productive development. Reliability is lower than needed for general consumer acceptance based on a comparison with gasoline station reliability, so reliability was identified as an ideal area for research and development. Data collected from retail hydrogen stations is incomplete and still a valuable source to explore methods for improving reliability. A promising option is a data-driven H2S PHM. The H2S PHM framework serves as the initial building block to develop a way to increase station availability and improve O&M costs. The H2S PHM could be adapted for an individual station or a network of stations, integrating a reliability survival analysis with economic trade-off of cost avoidance and revenue.

In order to be adopted by a station operator a clear operational benefit must be identified and model limitations addressed. The introduction of this model allows for validation and iteration as the throughput of hydrogen stations increases and more data is available. Other limitations of the data-driven H2S PHM can be mitigated with addition of more data, and possible advances in physics-based models and physics of failure findings. Recommended future research includes adding physics-based failure models, as well as iterating on the statistical models to decrease the prediction uncertainty. An analysis identifying the primary contributors to the uncertainty will highlight the priority areas for model improvements. A future economic optimization study will also identify the priority economic assumptions for use in the decision for deferred maintenance actions versus failure risk costs.

Looking toward the future requirements for a low cost of hydrogen per kilogram (and the exponential increase in hydrogen demand for multiple technologies), the H2S PHM model is expected to decrease maintenance-related cost contribution to the cost per kilogram. A decrease in cost is especially possible when the H2S PHM model is implemented in parallel with other developmental efforts like a component reliability improvement plan, specifically designed hydrogen components, and low-cost, high-volume manufacturing. Another impact that is not easily quantified is how an increase in station availability, driven in part because of the H2S PHM, could result in higher customer acceptance, thus improving the bottom line with both increased utilization and reduced O&M costs. Ultimately improved station availability with the H2S PHM increases confidence of FCEV drivers that the station will dispense hydrogen when requested, a needed step for continued market acceptance of FCEVs. Therefore, we can conclude that the application of traditional reliability engineering methods to a new field (hydrogen station operation) is one method that can address a leading challenge for hydrogen stations.

CHAPTER 7 – CONCLUSIONS

7. Summary

Hydrogen infrastructure to fuel light-duty passenger vehicles has moved from an idea to a reality. These hydrogen stations are fueling commercially available FCEVs, in the limited geographic regions where the stations are located. A review was completed in order to assess the hydrogen station technology status and improvements needed for the future hydrogen stations, both in California and for the national roll-out of hydrogen infrastructure and FCEVs.

While there are many research and development opportunities for hydrogen infrastructure, this research focused on a set of high priority technical challenges, station availability and dispensed hydrogen cost. This focus was selected because the review of station performance status identified because hydrogen station reliability is lower than the incumbent gasoline technology and the dispensed price of hydrogen is higher than the incumbent gasoline technology. In addition, these challenges were ideally suited to utilize a systems engineering process to identify possible solutions because the interrelationship of subsystems also influences reliability, cost, and the ability to successfully meet the consumer needs in a real-world setting

Hydrogen station reliability is directly related to availability and dispensed price, because unscheduled downtime reduces availability and adds cost due to maintenance. Both of these topics also have a direct relationship to consumer acceptance, which is necessary for successful commercialization of the hydrogen stations. Therefore, this research aimed to investigate systems level innovations that could improve availability and decrease cost by improvements to station reliability by reducing downtime and maintenance costs. I proposed that innovations like predicting the future fueling demand integrated with PHM would support O&M strategies needed to improve the commercial potential of hydrogen fueling stations.

7.1. Research Question Summary

The research set out to answer how can a measured and modeled hydrogen infrastructure system based on real-world operation be used to understand the benefit of integrating a new predictive reliability model to address key technical challenges of availability and cost. To answer this question, this research established the methods and framework for operational analysis and predicting demand and failures for a hydrogen station, through three smaller scope research questions, summarized as follows.

7.1.1 Research Question 1 – What is the measured operational performance of current, consumer-oriented, retail hydrogen stations?

The operation performance of current, consumer-oriented, retail hydrogen stations is safely filling FCEVs, with over 913,000 kilograms dispensed in 2018, having moved from a pre-commercial phase (prior to 2016) to an early commercial, retail phase. The number of retail (i.e., 24/7 publicly available) hydrogen stations is 39 in the U.S. supporting over 6,000 FCEVs. Safety is fully integration into station monitoring and control, with minor hydrogen leaks as the top category for safety reports. Hydrogen station capital costs of stations are approximately $5,000 per daily capacity (kg), which is much lower cost than the early demonstration stations in 2009 which had costs of approximately $20,000 per daily capacity. And new stations are being designed today that are expected to have lower costs. The hydrogen price at the pump is approximately 4 times the price of a gallon of gas. And a low MFBF negatively impacts station availability – a key consumer requirement – with unscheduled maintenance events and station downtime. This review of U.S. retail stations included deployment, safety, cost, fueling trends, and maintenance trends. The analysis identified four gaps (capital costs, reliability, multi-use (e.g., truck fills), and cost-effective renewable hydrogen) were observed as challenges for economically viable hydrogen stations.

Hydrogen station reliability has demonstrated improvements like lower maintenance costs and higher MFBF than the pre-commercial hydrogen demonstration stations. However, the station reliability is not as good as the incumbent gasoline fueling stations and station availability is a reported concern for FCEV owners. Hydrogen station reliability is a key influencer of hydrogen station market success. Cost and reliability gaps were the research motivation, focusing on how this research could improve reliability with hydrogen station system innovations that will increase availability and decrease cost.

7.1.2 Research Question 2 – What are the sources of potential for station controls and operations optimization to improve the economics and effectiveness of hydrogen stations?

The primary function of a hydrogen station is to safely and effectively transfer gas from the station to a FCEV. The hydrogen station has no control or insight of the FCEV demand, however. The FCEV driver is influenced by factors like accessibility to a station, FCEV tank level, hydrogen sourcing, and confidence in station availability. The industry has seen drastic changes in hydrogen fueling demand over the past 2-3 years with more FCEVs on the road and other applications like buses and trucks gain interest of fleet operators. Given the variability of hydrogen fueling demand in the future and critical demand is to the success of a hydrogen station, predicting future hydrogen demand has the potential to improve the economics and effectiveness of hydrogen stations. The predictions of fill trends (amount, frequency, and arrival time) by hour, day, and week guide station development and O&M strategies.

A hydrogen station design, permit, construction, and commission timeline can take more than a year according to the assessment of stations. This same assessment has also shown there are significant increases in demand in this same time frame of 1-2 years. A predictive hydrogen demand model allows a station operator to evaluate how well station configurations can dispense hydrogen for both near-term and future fueling demand. This can be accomplished by integrated the future demand with other station capability models (e.g., like a hydrogen capacity model [169] and hydrogen station equipment cost model [133]).

An unavailable station influences consumer confidence in hydrogen fueling as observed from fueling behavior trends and FCEV driver surveys. As consumer confidence is a factor in station demand, it is important for a station to maintain high consumer confidence. The predictive demand model allows for strategic station O&M decisions, like scheduling preventative maintenance at low use times and ensuring station storage state of charge is 100% prior to high use times.

7.1.3 Research Question 3 – What strategies for active hydrogen station health monitoring are actionable and effective at improving hydrogen station reliability?

There are multiple options for improving station reliability such as individual component reliability improvement programs and next-generation technologies. More holistically, this research proposes a framework for a hydrogen station prognostics health monitoring (H2S PHM) model that can minimize unexpected downtime by predicting the RUL for primary components. This H2S PHM is complementary to other reliability improvement efforts as it is implemented at the hydrogen station system level and can continue assessing when with multiple equipment generations and capabilities.

The H2S PHM model is a data-driven statistical model, based on O&M data collected from 34 hydrogen stations and more than 1,470,000 dispensed kilograms and 465,000 fills. The highest priority subsystems (determined by the most frequent maintenance activity) studied are the dispenser, compressor, and chiller. The RUL estimates are used to decide whether maintenance should be completed or not based on the prediction and expected future station use. The H2S PHM model is initially built on incomplete, real-world failures for a statistical model. This data is available for multiple stations as part of NFCTEC but is also tracked at each individual station, thus the statistics that are used to estimate the RUL for key components can be customized.

Answers from these three research questions have shown that hydrogen station system innovations such as predicting hydrogen demand and failures has the potential to improve station reliability. This is accomplished by proactive management of station downtime, economical preventative maintenance, and decreasing the number and frequency of unscheduled failures. As hydrogen station subsystems and components are still in an early commercialization phase so there is little publicly available research on component level physics-based failures so real-world O&M data is essential to the predictions.

This research is novel in part because of the combination of field hydrogen station performance benchmarking, reliability growth, predictive demand, and survival predictive analyses. A summary of the primary research contributions is:

- A survey of existing hydrogen station operation literature,
- A gap analysis to inform station requirements and operations to enable consumer acceptability, reliability, and reduction in the cost of delivered hydrogen,

- An analysis of a unique set of station O&M data from over 30 retail hydrogen stations in the U.S. There is no other published research that includes the amount and variety of real-world station data along with a focus on technical aspects of station O&M,
- A quantification of the reliability, consumer acceptability, and cost trade-offs associated with optimization of hydrogen station operations,
- A predictive fueling demand model, based on statistics of current hydrogen and incumbent gasoline fueling trends. The model is novel in that is the first to predict hydrogen fueling demand hour-by-hour and day-by-day,
- A H2S PHM model, based on statistics of hydrogen station maintenance events, particularly unscheduled failures. The model is built from over 465,000 fills and 5,600 maintenance records. An important model output is the estimate of RUL for high priority (based on current failures or impact) subsystems and components. This model is novel because it applies reliability engineering methods to reduce a hydrogen station's unscheduled failures and resulting downtime, and demonstrates the economic value of PHM in this new application,
- A set of peer-reviewed research material that provides new tools and methods to improve two leading challenges (availability and cost) for economically viable hydrogen station operations. A manuscript has been published in the International Journal of Hydrogen reviewing the operational performance of current, consumer-oriented, retail hydrogen stations, based on the first research question [145]. A manuscript covering the reliability analysis and real-world station status, is in the

final review stage. A manuscript covering the method and results of a predictive fueling demand model is in the review stage.

7.2. Future work

The suggested future work aims to address challenges with the proposed innovations and to build on the initial modeling framework with iteration, validation, and re-assessment. An example of a challenge is that the data the models are built on is from a variety of hydrogen stations in an early commercialization phase. The proposed innovations are only as good as the input data used to build the models, so additional data is needed. Therefore, one area for future work is continued model iterations with new and updated training data inputs from both real-world station O&M data, as well as laboratory benchmarking data.

Another area for future work is the addition of physics-based failure models that provide insight into the modes and indications for failure. A hybrid of both statistical data and physics-based models should improve the accuracy of predicting the RUL. The last recommendation for future work is to include more real-world economic values for component and system maintenance so that an optimization can be completed for the cost trade-offs waiting-to-maintain, preventative maintenance, and lost revenue due to unscheduled failures.

There are many hydrogen infrastructure variables that are rapidly changing, which challenges the assumptions and targets for hydrogen station reliability. The subsystem and component suppliers are improving designs and pushing the performance capabilities within a high-pressure hydrogen system so end-of-life criteria is not constant. New applications, such as heavy-duty fuel cell trucks, demand at least an order of magnitude increase in both fill amount and rate. New station operators are entering the market, which means that one-time errors that are avoided based on experience will likely be repeated. Reliability improvement programs that are adaptable and based on data and physics-based modeling are needed to ensure safe operation with this rapidly changing station configurations, capabilities, and requirements. Longer term future hydrogen station reliability engineering will have to include a more robust structure for spares, warranties, and technicians. This structure needs to be informed by the statistical models proposed here as well as reliability testing. The reliability testing should include failure root cause investigation and quality control features for critical subsystems and components, with run-to-failure data and accelerated failure benchmarking. The testing will also investigate and identify failure contributions due to mechanical, thermal, and humidity stresses, along with informed study on material capabilities when exposed to hydrogen. All the data from reliability modeling and testing will be used to direct customized hydrogen station designs for high reliability.

The extent of future reliability modeling and testing data that is expected will be an indicator of hydrogen stations commercialization and the required supply chain. With more reliability-based contributions from industry, government, and academics, the hydrogen station product will begin to model the function and reliability of other established gas infrastructures. Much of the reliability work proposed assumes continuity with current hydrogen station functions and operating requirements. Disrupting the status quo for hydrogen station function, design, and operating requirements is another compelling area for future work. Examples of future disruptive hydrogen station designs include high-pressure electrolyzer output (reducing or removing the need for compression), low-cost and safe bulk hydrogen storage in liquid and gas form. Research pushing the boundary of hydrogen stations component design and integration with other aspects of the energy systems (e.g., energy production, natural gas, industrial gas applications, cyber-security, and resiliency) should also include options to increase renewables on the grid, improve controls for optimal operation for reliability, and economically viable hydrogen infrastructure.

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